

Multimodal Approach for User Responsive Depression Detection

A Thesis submitted to Gujarat Technological University

For the Award of

Doctor of Philosophy

In

Electronics & Communication Engineering

By

ACHARYA JIGER PRAKASHCHANDRA

Enrollment No. 189999915002

Under supervision of

Dr. Milind S. Shah



GUJARAT TECHNOLOGICAL UNIVERSITY

AHMEDABAD

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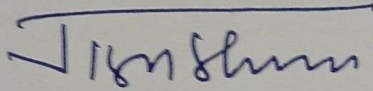
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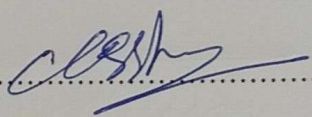
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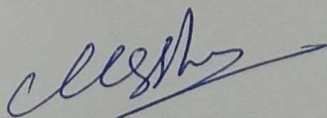
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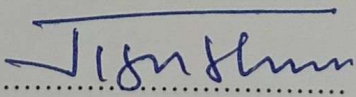


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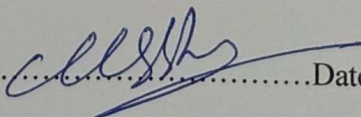
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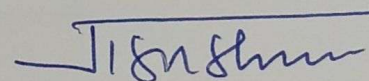
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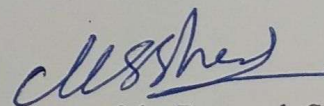
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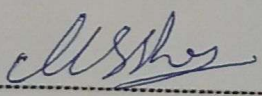
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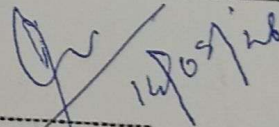
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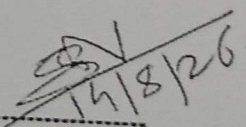
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ABSTRACT

Depression is leading cause of disability globally in all age groups which severely affects the global health index. During last one decade the mental health is becoming a major burning issue to society as number of various socioeconomic, personnel and societal issues related to mental health are increased in exponential manner. Depression is mood disorders which result in severe disabling conditions which affect person's ability to cope with routine life and real-life challenges which are dynamic in nature. It may occur when person remain more than two weeks in negative state of mind continuously. Depression has observable behavioral symptoms related to affective and psycho-motor domains which can be identified by human and/or computer. It is an ongoing problem which may resolve with proper care but may reoccur via various risk factors. The medical community does not fully understand the causes of depression but mostly known various risk factors like environmental factors, psychological, social factors, financial factors, drug addictions change in genetic features, brain's neurotransmitter levels, accidental events like major head injury and many more.

Early detection plays a crucial role as by positive counseling, various physical and mental exercises like meditation and proper medication may resolved depression else situations become worst up to suicidal tendency. Depression can be detected through various behavioral symptoms and during clinical interview by medical expert but the rate of the affected person reach at right time with right medical professional is very low so many researchers from physiological, pattern matching, computer vision have tried to detect depression features from behavior verbal and nonverbal channels with help of various of machine learning algorithms under Artificial Intelligence domain. Neural Network has shown shows great potential to resolve this burning issue of human health care domain to serve mankind.

Classical approaches majorly depend on person's behavioral analysis and family observations during clinical interviews, which are effective if it can be precisely defined and assessed but persons have tendency to conceal it so they are less effective so automated, real-time and friendly tool for pre-screening or early detection is highly needed in accordance to that we have analyze the various approaches like behavioral,clinical,bio-

instrumentation, visual, vocal, social-media text, colour psychology, deep neural network and questionnaires approach and considering main four factors

- Automated
- User-friendliness
- Real time user responsive and
- Multimodal in nature as

We have used Visual features of face, Self Response Inventory (S.R.I.) and colour psychology for depression detection purpose. We have proposed method of Deep Learning perform the said task with accuracy of 79 % open a user responsive simplified solution in mental health care domain of society.

As Depression or Depressive disorder is occur when person remains continuously in negative mood for more than 2 weeks' time person may converge to depression, we take first modality as input from visual features of face from static image and/or video either live or in stored form analyze facial visual feature to decide emotions or mood of the person. Second modality is taken in form of Self Response Inventory (S.R.I) based on past 2-3 days experience or feeling of the person based on respond to questionnaires approach and from the response of person he or she may be classified as in Normal, Mild, Moderate depression. Third modality called colour psychology is added to above questionnaires in which colour defines the emotions or mood of the person and based on these outcome present emotions or mood of the person is decided. If person get negative mood as outcome via all three modalities after time interval of 2-3 days again testing should execute and during 2 weeks of time repeatedly the negative mood reflects in outcome he or she should strongly advice to consult medical professional help for healing purpose.

This research is dedicated to such pre-diagnostic self-automated tool which can produced reliable result by performing fusion of available classical methods. This research is a novel approach which analyzes classical Self Response Inventory (S.R.I) and Visual features of person without intervention of other person so one can be more confidential and reliable result can be produced if tool is operated in an honest and truthful manner multi modal approaches give significant result so such automated tool really a boon in mental health care domain in near future for pre-screening of depression symptoms and can reduce the clinical burden and open a new era of mental health care domain.

Acknowledgement

I from bottom of my heart grateful to all Divine energies for giving me power and faith to start, sustain and complete this journey of research work. I remember the precious lines from Great Saint Kabirji...

मेरा मुझमें कुछ नहीं, जो कुछ है सो तोर ।
तेरा तुझको सौंपता, क्या लागै है मोर ॥१॥

भावार्थ – मेरे साईं, मुझमें मेरा तो कुछ भी नहीं, जो कुछ भी है, वह सब तेरा ही ।
तब, तेरी ही वस्तु तुझे सौंपते मेरा क्या लगता है, क्या आपत्ति हो सकती है मुझे ?

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ACHARYA JIGER PRAKASHCHANDRA
Research Scholar, Gujarat Technological University.

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List of Abbreviation

AFER	: Automatic Facial Expression Recognition
ANN	: Artificial Neural Network
AU	: Action Unit
BDI	: Beck Depression Inventory
BDI-S	: Beck Depression Inventory-Short
CES-D	: Centre for Epidemiologic Studies-Depression scale
CK+	: Extended Cohn-Kanade
CNN	: Convolutional Neural Network
DBN	: Deep Belief Network
DMI	: Depression Measurement Inventory
DNN	: Deep Neural Network
DL	: Deep Learning
DSM-5	: Diagnostic and Statistical Manual of Mental Disorder -5 th edition
EDA	: Electro-Dermal Activity
EEG	: Electroencephalogram
FER	: Facial Emotion Recognition
FC	: Fully-Connected
FGSVM	: Fine Gaussian Support Vector Machine
GUI	: Graphical User Interface
HRSD	: Hamilton Rating Scale for Depression
JAFFE	: Japanese Female Facial Expression
MOS	: Medical Outcome Study Depression Scale
KNN	: K-Nearest Neighbor
LBP	: Local Binary Pattern
LSTM	: Long Short-Term Memory
MDD	: Major Depressive Disorder
MER	: Multi-model Emotion Recognition
MLP	: Multi- Layer Perceptron
PHQ	: Patient Health Questionnaires
PPG	: Photoplethysmogram

List of Abbreviation

QIDS	: Quick Inventory of Depressive Symptomatology
QIDS-C	: Quick Inventory of Depressive Symptomatology-Clinical rating
QIDS-SR	: Quick Inventory of Depressive Symptomatology-Self Report
RF	: Random Forest
RNN	: Recurrent Neural Network
ROI	: Region Of Interest
SDDS-PC	: Self-Diagnostic Depression Scale-Primary Care
SRI	: Self-Response Inventory
SVM	: Support Vector Machine
zEMG	: Zygomaticus Electromyography

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CHAPTER-1

Introduction

1.1 Introduction to Depression

Depression or depressive disorder is related to mental health of a person which related to mood and / or emotions of a person. If down or depressed emotions or mood of a person prolonged more than two weeks person is identified in negative state of mind called depressive disorder or depression [1],[6]. Current or present states of mood or emotions are crucial check point for identification of depression. According to theory of emotions of Ekman [4] like theory of colour of wheel of colours where different colours are there, person also having various emotions or feelings positive, negative, neutral or mixed and it is changing continuously depending on internal and/or external feelings, emotions, experiences, affairs, situations and events.

Emotions related to person's attitude with nervous system to the external relations and / or based on the experimental and/or experiential learning outcome or feedback realized by person. As for example if person win the lottery of 10 million he or she will be delighted, happy or in positive mood but if he or she loss 10 million in stock market he or she will be in negative, down or feeling low mood. In any person's life human experience both experiences positive to enjoy, laughter and cherries while negative events, incidents or experience to cry but when person is trapped in down, negative, low mood continuously and such situation prolonged more than two weeks person is called in negative, down, depressed mood in medical terminology this situation is identified as depressive disorder called Depression.

The medical professional society still not fully recognize the causes of depression as they are subjective and vary case to case but major known risk factors are psychological, financial factors, environmental, societal, personnel etc. either internal or external.

1.2 Severity of Depression Globally

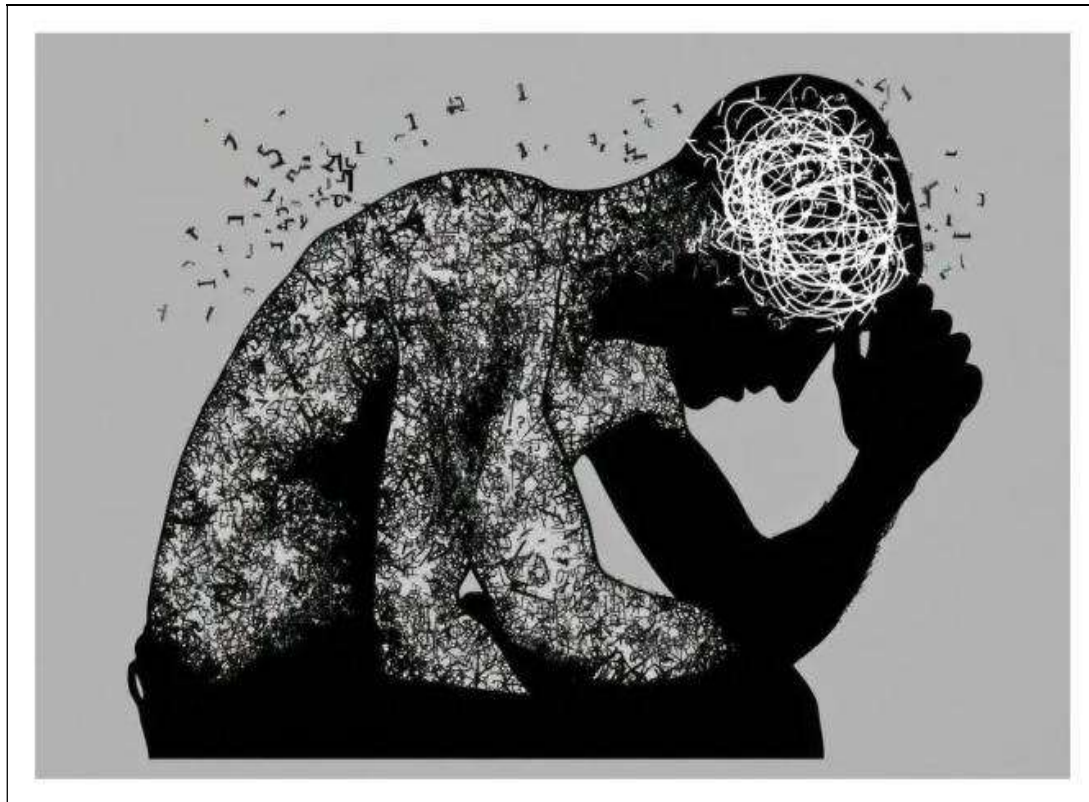


FIGURE 1.1: How stress moves from the mind to Body parts [52]

Depression is a mental health related issue which is leading cause of disability universally in each age groups which make severe effects on the personnel, societal and global health index and major impact on social routine. Figure 1.1 shows how Depression origin or start as mental health issue and slowly its adverse effect spread to whole body and in behavior. Depression known as an ongoing issue which may resolve with proper care with medication and/or meditation but may reoccur because of various risk factors. It can affect any age group according to research data in shown in paper [1] near 5% of global population more than 332 million people have depression from that 5.7% are adults in which 4.6% are males and 6.9% are females. From affected persons near 6% of people aged 70 years and older. 10% of woman experience depression during pregnancy the risk-factor is 1.5 compared to man as physical and psychological changes which woman has to pass before, during and after pregnancy process [2]. Depression is also 3rd leading cause of death in 15 to 29 years. Teenagers are vulnerable to depression as they experiencing biological changes and they have to cope up with more challenges and pressure like education, social, personal and societal permanence.

Figure 1.2 shows how Depression affects all age groups more than 7 million people suicide every year and 90% from them suffer from mental disorder. In high income countries only 1/3rd depress person receive mental health treatment [3]. More than 73% global suicide occurs in Low and medium income countries where quantity and quality of mental health care providers is a big challenge and more danger to that identification and acceptance of such mental health issues as ignorance of mental health and societal stigma .Affected person not aware or not accepting that they suffering such adverse conditions rather they try to act as normal person and try to manage all real life challenges to overcome and try to fight disabling conditions in real life. Depression ranges from mild, moderate to severe if it ignored and makes person’s life worst up-to such level that at last he or she accepts to quit life rather continuing fighting with real life challenges.

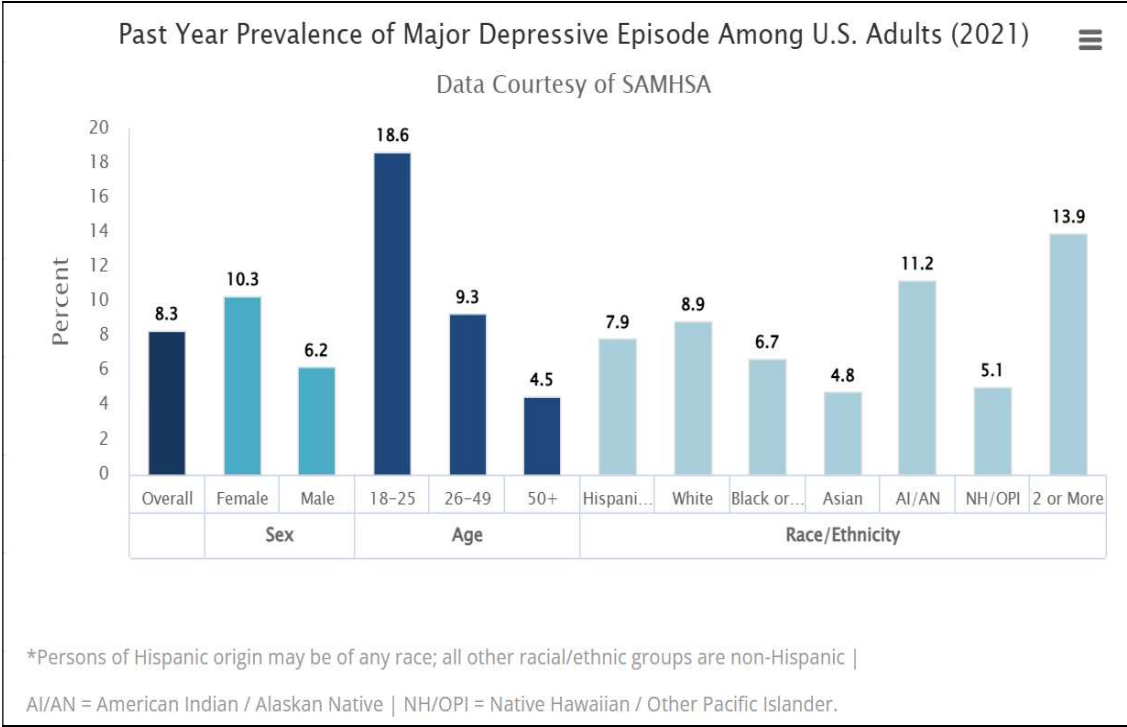


FIGURE 1.2: Global effect of Depressive disorder [43]

1.3 Early Depression detection “Easy to Cure”

Early detection plays a crucial role as by positive counseling, various physical and mental exercises like meditation and proper medication may resolve depression else situations become worst up to suicidal events. Human are expressive through verbal and

nonverbal communication channels both channels are important to express feelings [4], [5]. Person can remain silent to suppress verbal communication and by fake expression or conceal expression one can hide real scenario still researcher believes that facial expression is crucial input to present emotional status of person so psychologists try to map facial expressions to emotional states. When Person is feeling depression both verbal and nonverbal channel give strong indicators [6]. Number of researchers has contributed their work to identify depression which closely related with psychology, affective, computer and clinical domains so in real time it's a multi-challenging task.

As domain start with Psychology, Computer Science and Clinical domain and last long to social domain many key challenges required to address as under to map psychological domain to computer and validate it with behavioral / clinical predictions. If we can identify person's mood or emotions our goal achieved but it is a complex real-life problem as mood or emotions are internal and deeper it is human subjective representation also like Indian cricket team player Virat Kohli is very expressive or aggressive to show his emotions while M.S. Dhoni don't reflect his emotions like Virat means it is subjective aspects so vary from person to person. Many person may not comfortable to reflect his or her feelings to outside world easily or don't want to expose so he or she try to hide, conceal or suppress it in various situations which is a big challenge or issue and when person especially knowing that his or her behavior is monitored or evaluated he or she try to reflect what person want to show it may be not real but reel scenario like situation means acted behavior not real one.

By capturing human emotion, the psychological state of mind of any person can be identified and its related issues may be resolved so it's a high demand in real life situations where person's screen time is increasing and interactions with digital equipment is drastically increase. If computer or digital equipment can observe, fetch, analyze, and validate and can give feedback of emotions and/or mood of human accurately, that will be an excellent achievement in mental health care domain. Researcher expect the interactive machines which have the ability of observe, analyze and validate emotions same to human beings make machine emotional quotient and fulfilling emerging requirements of society.

1.4 Existing Practices and Approaches

Existing approaches majorly listed as

- (1) Behavioral approach
- (2) Psychological Approach
- (3) Clinical approach
- (4) Social media approach
- (5) Bio sensor instrument related approach
- (6) Multi modal approach

1.4.1 Behavioral Approach: Human are expressive through vernal and nonverbal channels for communication and express their feelings via both the channels but according to theory effective role of verbal communication is 7% only while remaining part is with nonverbal communications so it is the prime factor to identify person's behavior and related emotions. According to Argyle et al. [45] the functionality of nonverbal communications is as below.

A. Display emotional states (internal) and attitudes (external): we can identify emotional states or mood of internal feelings and attitudes toward outside situations from various non- verbal cues presenting from person which when we feel that nonverbal cues present from person conflicts be add on with his/her verbal communication.

B. Self presentation: The various non-verbal cues put impact on the way we present ourselves in particular situations and try to identify us in the minds of others. In addition, people judge us from the way we present ourselves at different situation, from our outer look or appearance, dressing, body movement, physic etc. Everything pertaining to self-presentation creates impression of ourselves in the presence of others.

C. The order and synchronization of communication: The non-verbal cues add routine interaction providing high correlation with verbal communication through which speaker appropriately take turn in speech and directs communication flow.

D. Reinforcement to spoken words: Non-verbal communication behaviors put more weight age on verbal messages and make communication more effective. Accompanying verbal messages with relevant non-verbal cues aids clarity of spoken messages and increase the probability of the receiver decoding the intended meaning.

E. Feedback: Non-verbal communication effectively conveys feedback without speaking a single word. From non-verbal cues reflecting from receivers of communicated messages, senders easily decode mindset of receiver and by recognizing the non-verbal cues presenting from individuals, others can easily predict the kind of conversation to follow and respond as the situation demands.

1.4.1.1 Visual Channel Base Approach: in field of image and/or video processing, computer vision, robotics, human computer interface, pattern matching and image processing community detect depression features from behavior visual behavior or appearance channels. Wager et al. [8], [9] revealed that depression can be decided by eye movement observation, and from the head and eye movement of person, the tendency of social withdrawal observed in manual and automatic mode. Cohn et al. [10] prove that during depressive disorder episode person's verbal and nonverbal communication channels affected drastically which can be proved during minute observations of subjective behavior analysis. When person is depressed both verbal and non-verbal channels are affected and give strong indicators.

1.4.1.2 Audio Base Approach: Ooi et al. [11] in 2013 proposed a system which automatically identify and measure audio channel related parameters for prediction of depressive disorder in near future which become crucial in identification of depressive disorder features in adolescents a novel approach of multichannel classification with accuracy of 73% in screening and produce a remarkable work on verbal channel approach executed by Cummins et al. [12] and Williamson et al. [13].

1.4.2 Psychological Colour Base Approach: Reveals how various colors affects person's mood and so on behavior called psychology of colors. In 2022 Yang et al. [32] enlightens colour co-relation with person's emotional response or mood based on age and cultural background. Major evidence is based on the feedback result of

anecdotal, but domain experts concluded that how colour theory relates with behaviors called colourpsychology. In 2020 Abu- Akel et al. [31] surveyed the emotional associations of 4598 persons from 30 countries and conclude that people commonly associate certain colour with specific emotions as presented in Table 1.1.

Table 1.1: Colour association with Emotion and Mood

Colour	Percentage	Emotions	Mood Category
Black	51%	Sad	Negative
White	43%	Relief	Positive
Red	68%	Love	Positive
Blue	35%	Relief	Positive
Green	39%	Contentment	Negative
Yellow	52%	Joy	Positive
Purple	25%	Pleasant	Positive
Brown	36%	disgust	Negative
Orange	44%	Joy	Positive
Pink	50%	Love	Positive

1.4.3 Clinical Base Approach: Person is critically diagnosed by medical professional based on response during real-time interaction with person and family member decision is made and psychological treatment and/or medication is applied. Major problem with this approach is quantity of such assessment is very low as person doesn't accept such mental health issues try to conceal or ignore such issues so approximately only 10% actually affected people get benefits of this approach.

1.4.4 Bio-Sensor Instrumentation Base Approach: in which various biomedical instruments and sensors can be used to identify the person's behavioral and / or biological analysis but user acceptability of such approach is very less. Such sensor like EEG, EDA, PPG, zEMG sensors provide a comprehensive picture of human nervous system. EEG measure brain's electrical activity using electrodes place on scalp. EDA (Electrodermal Activity) measure changes in the electrical conductivity of skin also known as Galvanic Skin Response. Photoplethysmography (PPG) measure blood volume changes in the microvascular bed of tissue, usually recorded via light absorption on a finger or earlobe. Evaluate autonomic nervous system function, providing critical data on relaxation states and cognitive stress. It is a convenient method for monitoring oxygen saturation and pulse. zEMG (Zygomaticus

Electromyography) measure the cheek muscle responsible for smiling and help to differentiate positive and negative emotional valence. Above sensor's received psychological signals measured in real time manner which cannot be suppress or conceal like audio, video or textual information's so the reliability of such system is very high but acceptability is very poor because of its complex or non-user-friendly testing procedure.

1.4.5 Social Media Base Approach: in present era of virtual world of digital community or social networking platform person spare most of the time on screen so social media like face book, twitter, Instagram, snaps etc. In such social networking and virtual world platform people put their mood and emotions in form of status, text message and images. Uploaded images and associated tag person's mood can be categorized from text messages, pictures or emoji person's mood can be predicted [30].

1.4.6 Multimodal Approach: Many contributors' fuses single modality into multimodal approach in which person's data from multiple channels are evaluated make emotion or mood detection more accurate and reliable compared to single modality system [41].

1.5 Emotion Theories

Definition of emotions in scientific context is a fundamental problem in the psychology domain as affective domain emotions required to be defined by scientific domain. There are many definitions of emotion which classified as: the "basic emotions" and the "appraisal" approaches [47]. Figure1.3 represent the two-dimensional emotion system in which despite the subjective variability of the emotional responses, cognitive, and cultural variations, basic emotions models remain universal and precisely identify psychophysiological states of the person. The main underlying assumption in the basic emotions' approach [48], is emotions belonged to the same class may vary in intensity or other corresponding dimensions, but share comparable behavioral pattern in term of responses, biological analogy behavioral patterns, body reaction, and facial expressions. This approach identifies group of similar emotions with the common most appropriate prototypical one for example "happy" contains "joy", "enjoyment", "pleasure", etc.

On the other hand, appraisal-based approaches believe that emotions activated by a physiological body response derives from a subjective interpretation during the specific situation based on personal criteria.

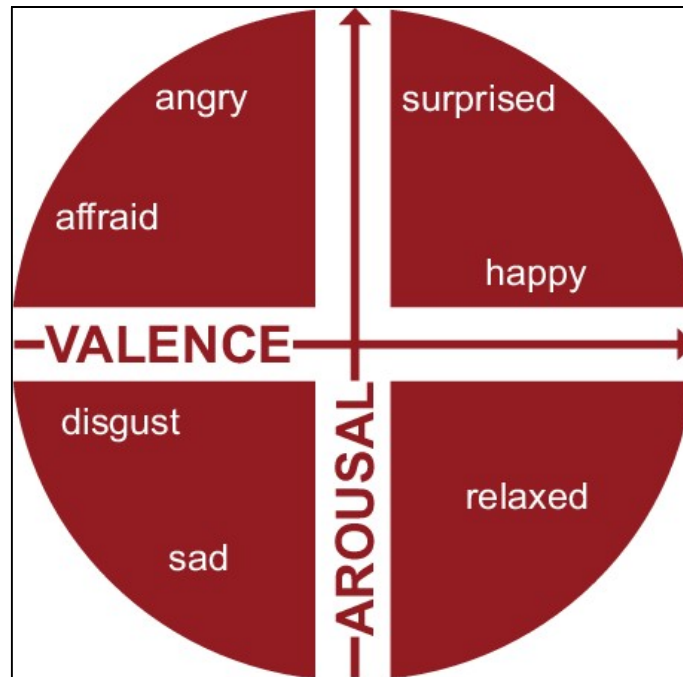


FIGURE 1.3: Two-dimension emotion system [46]

In Discrete Emotions theory model various emotions are used in the field of Affective Computing or Emotional Intelligent system in which various facial expression-based recognition system emotions are extracted. Numbers of models of prototypic human emotions exist, differing from each other in the number and the type of identified emotions. Some wide spread criteria to recognize basic emotion from non-basic ones are:

- 1) a universally acceptance and/or recognition of facial expression,
- 2) quick recognition, and
- 3) a unique subjective feeling [48].

Till date, the most acceptable models of discrete emotions in the scientific research community belonged to the theories of Ekman, Izard, Oatley, Johnson-Laird, Plutchik, and Tomkins [47]. Dimensional Emotional Models in neuroscience research community prove that emotions can be majorly divided into discrete and independent categories. Dimensional theories assume that all affective states derive from common neuro physiological systems. So, each emotion can be represented as a mixture of such systems, also called as dimensions.

Popular dimensional theories widely accepted by the research community, are as under.

The model of emotions of Russell the first and most popular dimensional models identify two independent dimensions: valence and arousal, represented as the two dimensions of a plane in which 28 different emotions are mapped in a circular pattern. The arousal-non-arousal scale calculates the intensity of emotion and constitutes on the Y- axis of the representation system. The points corresponding to the upper semi circle are classified as high arousal, while the points corresponding to the inferior semi-circumference are called low arousal. Valence on the X- axis measured on pleasure-displeasure scales, which calculate the amount of pleasure of an emotion. On the left semi-circumference, unpleasant emotions like angry, afraid, sad and disgust are shown, while on the right semi-circumference pleasant emotions like happy, relaxed and surprised are represented in Figure 1.3. Some hybrid models, like the Plutchik which fuse the both approaches [47].

1.6 Deep Learning Basics

Deep Learning is a subset of Machine Learning which train computers to solve real-life complex problems by copying human brain's ability called intelligence. It uses multiple layer architecture to find hidden patterns from the data. These computational methods known as Artificial Neural Network (ANN) under AI domain. The components of such networks are layers, connections and activation functions.

- (1) Layers: The network is made of multiple layers where each layer contains a set of number of processing units called neurons. The layer which accepts the input data known as Input layer. The last layer or final groups of neurons which produce outcome or result called Output layer. The layers between I / O layers are called hidden layers which breakdown complex task in step-by-step task, process or transformation where each step extract specific details from data.
- (2) Connections: Every neuron interconnected with other neurons. The output of one neuron become input for next one.
- (3) Activation functions: These are specific mathematical rules which determine how neurons pass information to each other.

Figure 1.4 shows Deep learning Model for Human Face Recognition model.

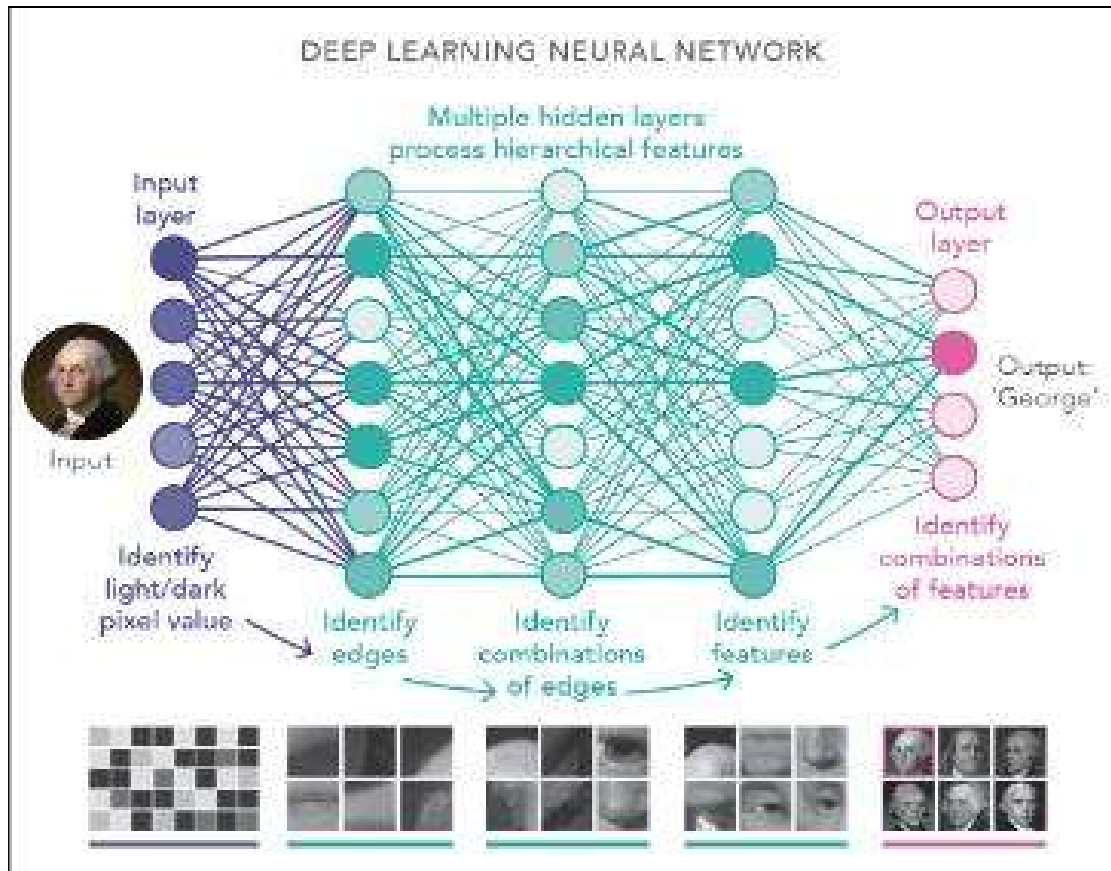


FIGURE 1.4: Deep Learning Model for Human Face Recognition [53]

1.7 Convolutional Neural Networks (CNN)

Convolutional Neural Networks are specific networks consist of one or multiple layers which contains units which are implementing convolutional operations for transforming the input data. The goal of convolving the information through the network layers to analyze and capture the data of specific regions to create various recognition patterns. The convolutional layers have trainable weights and biases but the size and dimensions of them are majorly depend on the type of convolution used for the layers. The convolutional architectures in Deep Learning have gained focused since last 15 years. The convolution layers are generally implemented along with pooling layers, to reduce the size of the characteristic subspace called computational cost and avoid the over fitting problem in the network layers. Figure 1.5 represents the typical CNN model for input image classification purpose.

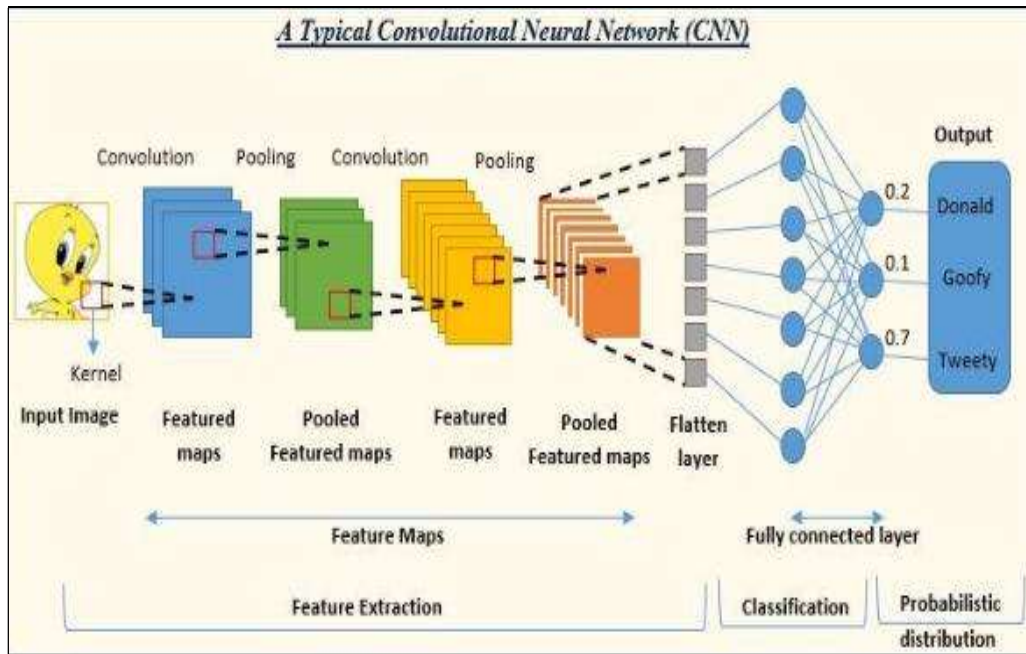


FIGURE 1.5: Convolutional Neural Network Model [54]

1.8 Model Performance Metrics

Several mathematical techniques used to compute the performance of a computational model in a various classification approach problem. A confusion matrix shows the performance of a supervised machine-learning algorithm. A problem with m classes classification requires a $(m \times m)$ confusion matrix where the rows representing the actual class and the columns represent the class predicted by the model. Figure 1.6 is an example of a confusion matrix.

		Actual Values	
		Positive (1)	Negative (0)
Predicted Values	Positive (1)	TP	FP
	Negative (0)	FN	TN

FIGURE 1.6: Confusion matrix for binary classification

In common, the confusion matrix gives four types of classification outcomes for a particular class m:

True Positives (TP): In which both predicted and actual classes are class m

True Negatives (TN): where both predicted and actual classes are not belonged to class m

False Positives (FP): where Predicted class is class m, but the actual class is not belonged to class m.

False Negatives (FN): Predicted class is not m, but the actual class belong to class m.

From the confusion matrix performance parameters like precision, recall, and F1-score are defined as under.

Precision called the percentage which model correctly predicts positive when making a decision as below equation (1)

$$\text{Precision} = \text{TP} / \text{TP} + \text{FP} \dots\dots\dots (1)$$

Recall defined as sensitivity which measure as percentage of positives correctly identify out of all the existing positives as below equation (2)

$$\text{Recall} = \text{TP} / \text{TP} + \text{FN} \dots\dots\dots (2)$$

Accuracy = Total no of correct predictions / all predictions

$$\text{Accuracy} = \text{TP} + \text{TN} / \text{TP} + \text{TN} + \text{FP} + \text{FN} \dots\dots\dots (3)$$

F1 - score called harmonic mean of the precision and recall

$$\text{F1-score} = 2 \times \text{Precision} \times \text{Recall} / \text{Precision} + \text{Recall} \dots\dots\dots (4)$$

1.9 Proposed System:

We proposed an automatic tool for depression detection. As it is self operated person is in-front of that tool alone so no external interference and he or she can express own self or behave naturally with real feelings or mood it reduces the burden of continuous human monitoring or intervention and clinical burden also. This multi-modal tool identifies person's current mood or emotions which are real time, user responsive and automatic.

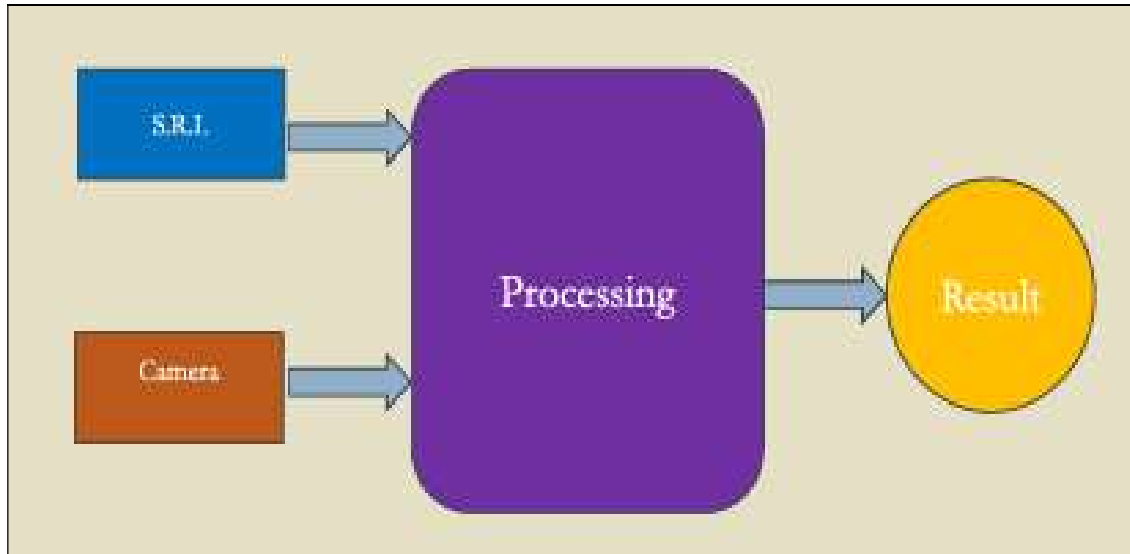


FIGURE 1.7 Block diagram of Proposed System for Depression Detection

Figure 1.7 shows block diagram of Proposed System which take one input from camera in the form of static and video process the visual features and recognize the emotions of person from visual data and categorize them into positive (Happy), Negative (Sad, Disgust, Contempt, Angry, Fear) Surprise expression may converge to both positive or negative dimensions and Neutral expression has unbiased to positive and negative theory.

If person is getting positive emotion as outcome means person is feeling positive mood and according to the definition of depression if person continuously feeling down, negative suppressed mood for more than two weeks he or she may converge to depressive mood disorder or depression so if person getting positive emotions as outcome no need to worry about depression but condition is that screening tests must be real means no fake expression should be acted by the person under screening test.

Second input to processing unit is Self Response Inventory (S.R.I.) which is a unique collection of questionnaires selected to check the person's physical and mental health. As depression alters the pattern of food, sleep, rest, and mental ability also so if these questions are responded truthfully depending on this basis also, we can conclude the mood of person so it is the second criteria in deciding the feeling emotions of the person under screening test.

In above questionnaires one question particularly related colour psychology is included and based on that we can also decided the mood or emotions of the person in this theory colour used as deciding parameter of psychology so outcome of colour decide the positive or negative emotions or mood.

Based on the outcome of above all three channel of screening person's emotions, mood can be decided and if all are converge to negative the person is in negative, suppressed or down mood and if such results are repetitively same within in two week of screening time person is converging and/or already stuck in mental health related issues and required to consult mental health care provider immediately for healing purpose.

1.10 Outline of the Thesis

The remaining thesis is organized in the following chapters:

Chapter 2(Literature Review) Provides background information related to the research topic with an extensive literature survey of the various methods and approaches used till now. It outlines the shortcomings of these methods, approaches. From this literature survey we conclude our research direction to identified problem statement and objective of the research work finalized.

Chapter 3(Approaches for Depression Detection) in this chapter, various approaches are discussed with their details which will be helpful in selecting the modalities for the proposed system.

Chapter 4 (Proposed System Approach) this chapter represent proposed architecture with details of Multi modal Approach for User Responsive Depression Detection tool or system in depth with performance parameter and statistical analysis.

Chapters 5 include the Conclusion of work, the future scope of the work and major contribution of the thesis supported by journal publications and references.

CHAPTER-2

Literature Review

2.1 Introduction

Recognition depression and validating it be an important and crucial part for improving the human computer interactions. Mainly various researcher from Psychology, Clinical, Computer science and social domain have reported their research work related to emotion, mood or depression recognition presented in Table 2.1.

Table 2.1: Researchers contribution of domain related research

Sr no	Researcher	Modality	Instrument/ Dataset
1	Hamilton et al. (1960)	Questionnaires based rating scale for depression analysis	Psychiatry questionnaires based Self-reported tool for depression analysis
2	Zung et al. (1965)	Questionnaires based rating scale for depression analysis	Psychiatry based tool for depression analysis
3	Radloff et al. (1977) Center for Epidemiologic Studies Depression Scale (CES-D)	Questionnaires based rating scale for depression analysis	CES-D A Psychological based self-report tool of 20 questions for depression analysis
3A	Center for Epidemiologic Studies Depression Scale-Short Form (CES-D-short),1997	Short Questionnaires based rating scale for depression analysis	CES-D-Short A Psychological based self-report tool of 10 questions for depression analysis
4	Beck et al. Beck Depression Inventory (BDI-1961)	Questionnaires approach, Beck Depression Inventory (BDI)	BDI Psychiatry assessment-based personality tool of 21 questions for depression analysis
4A	Beck Depression Inventory-Short Form (BDI- Short),1978	Beck Depression Inventory-Short Form (BDI- Short),1978	BDI-S Psychiatry assessment-based personality tool of 13 questions for depression analysis

Sr no	Researcher	Modality	Instrument/ Dataset
5	Williams et al. (1999) PHQ-9, PHQ-2	Patient Health Questionnaire-9, (PHQ-9)	PHQ-9 self-report tool of 9 questions related to depression analysis
5A	Williams et al. PHQ-2	Patient Health Questionnaire-2, (PHQ-2)	PHQ-2 self-report tool of 2 questions related to depression analysis
6	Rollin Nagel MA et al. Medical Outcome Study- Depression Scale (MOS),1992	Medical Outcome Study- Depression Scale (MOS),1992	MOS self-report tool of 8 questions related to depression analysis
7	Developed by Primary Care Physicians Self-Diagnostic Depression Scale Primary Care (SDDS-PC),1994	Self-Diagnostic Depression Scale Primary Care (SDDS-PC),1994	SDDS-PC self-report tool of 7 questions related to depression analysis
8	Trivedi et al. (2003) Quick Inventory of Depressive Symptomatology, (QIDS)	Quick Inventory of Depressive Symptomatology, (QIDS),2003	QIDS 16 items quick inventory for depression symptoms assessment
9	Parker et al. (2004) Depression Measure Inventory -10 (DMI-10)	Depression Measure Inventory-10 (DMI- 10),2004	DMI-10 , self-report tool of 10 questions related to depression analysis
10	Becker et al. (1994)	Audio/Video	Dementia Bank Database Reddit Self-reported
11	Valstar et al. (2013)	Audio/Video	AVEC 2013
12	Pradhan et al. (2014)	Text data	SemEval-2014 Task 7
13	Lieberman et al. (2013)	Text data	Crisis Text Line
14	Valstar et al. (2014)	Audio/Video	AVEC 2014
15	Gratch J et al. (2014)	Audio/Video	The Distress Analysis Interview Corpus
16	Valstar et al. (2016)	Audio/Video	AVEC 2016
17	Videbech (2016)	Audio/Video /Report	The Danish Depression Database

Sr no	Researcher	Modality	Instrument/ Dataset
18	Yates et al. (2017)	Text data	Depression Diagnosis (RSDD) dataset
19	Garcia-Ceja et al. (2018)	Audio/Video	Depression
20	Komal Anadkat et al. (2022)	Audio / Video / EEG Social media text	FER2013, Ravdess, Kaggle's social media dataset, and EEG dataset

Existing approaches majorly listed as

- (1) Clinical Approach
- (2) Behavioral Approach
- (3) Psychological Approach
- (4) Social media Approach
- (5) Bio sensor instrument related Approach
- (6) Multi modal Approach

From above all we have selected to fuse first three approaches as Questionnaires approach in which details questions related to physical and mental health of a person along with colour selections decide the mood of the person and based on responses or score person mental health is decided.

Second approach is of Facial Visual feature-based approach in which based on the facial expression of the person person's expressions and from that emotions or mood is decided so detailed literature study of these approaches is as below.

2.2 Literature Reviews of Visual Channel Base Approach:

Computer vision, pattern matching and image processing community detect depression features from behavior visual channels. Wager et al. [9] revealed that depression can be judge by head and pose movement of person and which also reveals the tendency of social communication and social withdrawal may be judge from human expert manually and/or automatic analysis. Cohn et al. [10] outline that during depressive disorder verbal and nonverbal channels are majorly affected which can be judge during minute external observations. When person is depressed both verbal and non-verbal channels affected and

give strong indicators.

Facial expression plays key role for to identify emotions of human as humans are mostly communicate via facial channel and landmarks like nose, eyebrows, eyes and mouth play a vital role in non-verbal communication Ekman et al. [48], considered this research categorize six basic emotions, e.g., Anger, Joy, Sadness, Disgust and Surprise from facial expressions.

Before the invention of deep neural networks, various machine learning techniques are used to extract the facial features from still images or sequential frames from video. It is very difficult to extract the features manually as it requires depth domain knowledge and lots of efforts. Deep learning based facial emotion recognition extract the features automatically and easily. Using deep learning is like “Black box”, as neural network not disclose how the features are extracted. Deep-learning algorithms are widely popular for the purpose of feature extraction, classification and many computer vision tasks because of user friendliness.

Talipu et al. [49] fused datasets like CK+, FER and affectnet. As fusion give better accuracy as CK+ and FER are real life dataset. Jain et al. [51] proposed Residuals network after alternate convolution layer for achieving higher accuracy. Major literature review on visual feature approach is presented in Table 2.2.

Table 2.2: Literature Review on Visual Feature Base Approach

Author(s)	Key work	Methodology	Performance Results	Limitations
A. Talipu. et al. [49] IEEE 23rd International Symposium on Consumer Technologies (ISCT), 2019	“Evaluation of deep convolutional neural network architectures for emotion recognition in the wild,” 2019	CK+, Oulu-CASIA, and MMI Data set, RNN classifier and Normalization, Dropout done.	Highest accuracy 98.50% with CK+ dataset and 81.18% with MMI.	Accuracy of fear, sad is low

Author(s)	Key work	Methodology	Performance Results	Limitations
B. Taha et al. [50], “Emotion recognition from 2D facial expressions,” 2019	Emotion Recognition from Facial Expression 2D	Bospor us dataset, Data augmentation, dropout done,	CNN with SVM classifier used Accuracy 92.14% for happy when CNN with SVM.	Dataset of static frames
K. Jain et al. [51] Pattern Recognition Letters, vol. 120, pp. 69–74, Apr. 2019	Extended deep neural network for facial emotion recognition	CNN on Wild dataset, CK+FER+ Affectnet	Facial alignment on merged data set preprocessing done; The best accuracy is achieved by the VGG13 architecture 75.48%.	Facial expression accuracy for fear, disgust is low mainly Static images

2.3 Literature Reviews of Questionnaires Base Approach:

In this approach question related to mental health and physical health and routine-life questions are asked by medical professional to patient or family members based on the response the physical and mental activeness of person is decided and person categorize as Normal or with mental health related issues in scale of mild, moderate or severe some of well-known 10 such instruments which are earlier used are mentioned below.

2.3.1 Hamilton Rating Scale for Depression (HRSD): Hamilton et al. [33] proposed HAM-D which is MCQ type questionnaires which medical experts utilize for depression severity assessment.

2.3.2 Zung Self–Rating Depression Scale: Zung [37] proposed a short survey which identify depression levels called Zung Self Rating Depression Scale.

2.3.3 Centre for Epidemiologic Studies-Depression Scale (CES-D): Radloff [38]

proposed a self-reported scale with 20 questions designed for mental health care givers to measure depression symptoms. A higher score can help doctor to identify severity of depression.

2.3.4 Beck Depression Inventory (BDI): Beck et al. [34] proposed a self - reported instrument is available which consist of 21 questions MCQ type questions. The self-report decides severity of depression symptoms based on the response given.

2.3.5 Beck Depression Inventory (BDI- Short): In 1978 above, self-reported instrument optimized as short version of BDI called BDI- Short in which 21 questions are reduced with 13 only e questions types self-report which calculate the severity of depression from response given.

2.3.6 Patient Health Questionnaires (PHQs): Kroenke et al. [35] proposed the most accepted and popular tool called PHQ - 9 which has nine questions about person's mood and daily routines like appetite, sleep and daily activities the response of these helps doctor come to a depression diagnosis. The PHQ - 2 asks the first two questions of the PHQ - 9 which is a screening test guide doctor for further processing.

2.3.7 Quick Inventory of Depressive Symptomatology (QIDS): In 2003 QIDS is a clinical and/or self reported tool for depression analysis in which 16 questions related to mental health are asked and based on response depression level is decided.

Whooley et al. [39] analyze the result analysis of seven Depression Case finding instruments on 536 person's and concluded that only two questions:

- (1) "During the past month, have you often bothered by feeling down, depressed or hopeless?"
- (2) "During the past month, have you often been bothered by little interest or pleasure in doing things?"

are enough to detect depression but in such case the false positive rate may be high so by analyzing all above tools for depression detection tool we have proposed a Self-Response Inventory (S.R.I.) based self-assessment tool for depression.

2.3.8. Self –Response Inventory (S.R.I): S.R.I is quiz-based approach in which person asked to respond quiz truthfully based on past 2-3 experience or feelings based on response additive score of quiz mental health is decided. S.R.I quiz has unique specific questionnaires related with physical and mental health of a person and based on the response it categorizes person’s mood in Normal, Mild, Moderate and Severe Negative mood.

Table 2.3 represent comparative study of existing questionnaires approach and Table 2.4 represent Literature review on it.

Table 2.3: Comparative study of existing Questionnaires Approach

Sr no	Tool with timeline	Type	Questions	Classification
1	Beck Depression Inventory (BDI),1961	Self-report	21	0-13: Min 14-19: Mild 20-28: Moderate 29-63: Severe
2	Beck Depression Inventory-Short Form (BDI-Short),1978	Self-report	13	0-4: Minimal 5 -7: Mild 8 - 15: Moderate >15: Severe
3	Center for Epidemiologic Studies Depression Scale (CES-D),1977	Self-report	20	< 16: Minimal 16-26: Mild-Moderate >26: Severe
4	Center for Epidemiologic Studies Depression Scale-Short Form (CES-D-S), 97	Self-report	10	< 10: Minimal 10-14: Mild > 14: Severe
5	Medical Outcome Study-Depression Scale (MOS),1992	Self-report	8	Low Score: Normal Medium Score: Mild High Score: Higher
6	Self-Diagnostic Depression Scale Primary Care (SDDS-PC),1994	Self-report	7	0-2: Normal 3-4: Mild 5-7: Severe
7	Patient Health Questionnaire-9, (PHQ-9),2001	Self-report	9	0-4: Minimal 5-9: Mild 10-14: Moderate 15-19: Mod-Severe 20-27: Severe

Sr no	Tool with timeline	Type	Questions	Classification
8	Quick Inventory of Depressive Symptomatology, (QIDS),2003	Clinician/Self	16	0-5: None 6 -10: Mild 11-15: Moderate 16-20: Severe 21-27: Very Severe
9	Depression Measure Inventory -10 (DMI-10),2004	Self-report	10	0-7: Normal 8-14: Mild Moderate 15-20: Moderate >20: Severe
10	Proposed (Self Response Inventory) S.R.I.	Self-report	21	0-4: Normal 5-8: Mild 9-14: Moderate >14: Severe

Table 2.4: Literature Review on Questionnaires Approach

Author(s)	Key work	Methodology	Performance Results	Limitations
Williams JB. et al. [35] Journal of General Internal Med. 2001	The PHQ-9: validity of a brief depression severity measurement	Classical, standardize and clinical questionnaires approach	PHQ-9 scores of 5, 10, 15, 20 represented mild, moderate, moderately severe, and severe depression	Proven standardized approach May have Higher False Positive ratio
PHQ-9 MDD module of the full PHQ et al. Levis B et al. [36] 2019	Accuracy of Patient Health Questionnaire-9 (PHQ-9) for screening to detect major depression: individual participant data	Diagnose grade severity of symptoms Scores each of the 9 DSM criteria of MDD on 0-27 severity score.	High score decreased functional status and increased symptom-related issues.	May high false-positive (50%) positive actually had major depression

Author(s)	Key work	Methodology	Performance Results	Limitations
Browner, S. et al. [39] Journal of General Internal Medicine, 12: 439-445. 1997	Case-Finding Instruments for expression: Two questions Are as Good as Many	Classical, standardize and clinical questionnaires approach Result Analysis of Seven Depression Case finding Instrument on 536 subjects	(1) “During the past month, have you often been bothered by feeling down, depressed, or hopeless?” (2) “During the past month, have you often been bothered by little interest or pleasure in doing things?”	Result relies on response of 2 answers only May have Higher False Positive ratio
Trivedi MH, et al. [40] psychometric evaluation in patients with chronic major depression. Bio Psychiatry. 2003	The 16-Item Quick Inventory of Depressive Symptomatology (QIDS), clinician rating (QIDS-C), and self-report (QIDS-SR NO)	QIDS, QIDS-C, QIDS-SR NO	16-item quick inventory of depressive symptom clinician rating and self-report for psychometric evaluation in patients with chronic major depression	Alarming rate of false detection

2.4 Literature Reviews of Psychological Colour-Based Approach:

In this approach Colour used as emotion identifier and also used as therapy. It reveals how various colours impact person’s mood and so behaviors. Yang et al. [32] enlightens colour impact on person’s emotional response based on age and cultural background etc. Major evidence in this emerging area is based on the feedback result of anecdotal, but domain expert has made a few important conclusions that how colour theory correlate with behaviors. Abu- Akel et al. [31] surveyed the emotional associations of 4598 persons from 30 countries and conclude that people commonly associate certain colours with specific emotions.

As shown in Figure 2.1 we selected red colour for representing positive emotion

(love) with 68% and black colour to identified negative mood related to sad emotion with 51% so based on selection from either Black or Red colour we can decide the emotion or mood of the person as negative or positive. If no colour selection is selected we neutralized the mood neither positive nor negative. Detailed literature review of approach is mentioned in Table 2.5.

Colour based Emotions association		
Colour	Percentage	Emotions
BLACK	51 %	Sad (-)
White	43 %	Relief
Red	68 %	Love(+)
Blue	35 %	Relief
Green	39 %	Contentment(-)
Yellow	52 %	Joy(+)
Purple	25 %	Pleasant(+)
Brown	36 %	Disgust(-)
Orange	44 %	Joy (+)
Pink	50 %	Love (+)

FIGURE 2.1: Colour association with Emotions [43]
Table 2.5: Literature Review on Colour Base Psychology.

Author(s)	Key work	Methodology	Performance Results	Limitations
Abu-Akel A et al. [31] Psychol Sci. 2020;31(10):1245-1260.	Universal patterns in colour-emotions further related with linguistic and geographic proximity	Explore the association of emotion with colour in Affective communication.	2020 research study surveyed emotional associations of 4,598 people from 30 countries concluded people associate certain colour with specific emotions.	According to results black colour associated 51% with negative emotion Red colour associated with 68% with positive emotions

Author(s)	Key work	Methodology	Performance Results	Limitations
Yang J, Shen X et al. [32] J Environ Public Health. 2022	Application of colour psychology in community health environment design	Symbolic meaning of each colour is revealed	Conclude that colour can be used as therapy	Red spectrum part led comfort to anger while blue described calm evokes feelings of sadness.

2.5 Literature Reviews of Multi-Modal Approach:

Many contributors' as mentioned in Table 2.5 fuses various single modalities into multi modal approach in which person's data from multiple channels are evaluated make emotion or mood detection more accurate and reliable.

Cohn et al. [10] first to introduced Automated tool for Depression Detection which reduce human participation and burden and concluded that depression reduce affiliative behavior like motivation, co-operation, comfort and request etc.

Sahla et al. [20] and / or Venkataraman et al. [24] used uni-modal approach and select Visual features used for depression detection.

Komal et al. [30] used single modality as social media status for emotion recognition later fused three modalities Visual feature, Audio and EEG for emotion recognition.

Priyasad et al. [28] fused audio and text feature for emotion recognition.

Tzirakis et al. [22] fuse text, visual and audio features in end-to-end Deep Neural Network and find out emotions' recognition.

Sahay et al. [23] fused three modalities called text, audio and video for emotion classification.

Hassan et al. [27] performed emotion recognition through Deep Belief Network

(DBN) used Bio- sensor instrumentation approach with EDA, PPG, zEMG sensors fused their data for emotion recognition.

Njoku et al. [29] fused visual, vocal and physiological EEG signal data for emotion recognition.

Yang et al. [41] fused visual, audio and text signals with learning and knowledge transfer with Autoencoder.

After reviewing all above we proposed an automatic tool for person behavior detection based is crucial as person is in-front of that tool alone no external interference so he or she can express own self or behave naturally what he or she feels it again reduce the burden of continuous human monitoring or intervention by realizing this fact we developed an automated tool for human behavior analysis to identify person's current mood which is real time, user responsive and automatic. Overall literature review of proposed research topic listed in Table 2.6.

Table 2.6: Overall, Domain related Literature Review Analysis.

Author(s)	Key work	Methodology	Performance Results	Limitations
Jeffrey F Cohn et al. [10] Image and vision computing, pp. 641-647, 2014	Nonverbal social withdrawal in depression: Evidence from manual and automatic analyses	Automated tool for FER	Depress person reduced affiliative behavior like motivation to co-operate, comfort and request etc.	Automatic facial expression analysis can reduce human participation and burden.
Sahla, K. S et al. [20] International Symposium on Intelligent systems Technologies and Applications, pp. 475-486. Springer	Classroom Teaching Assessment Based on Student Emotions	Emotion analysis of students from visual channel	face detection, LBP encoding and mapping using deep CNN	Uni modal Visual feature approach

Author(s)	Key work	Methodology	Performance Results	Limitations
Dr. D. Venkataraman et al. [24] International Journal of Pure and Applied Mathematics Volume 118 No. 7 2018, 455-463	Extraction of Facial Features for Depression Detection among Students	Automated tool for Depression detection applied in classroom T/L environment.	Automated system pick students via captures frontal face videos, extracts facial features from frame analyses to detect signs of depression	trained with frontal face images of Happy, Contempt and Disgust faces
Priyasad et al. [28] IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2020	Attention driven fusion for multi-modal emotion recognition	Emotion recognition using acoustic and text	SincNet layer and DCNN for acoustic feature extraction and parallel DCNN and Bi-directional RNN branches with cross-attention for text processing.	Emotion recognition using acoustic and text
Tzirakis et al. [22] IEEE Journal of Selected Topics in Signal Processing, vol. 11, no. 8, pp. 1301–1309	End to-End Multi-modal Emotion Recognition Using D.N.N.	Deep Neural Network	Work fuses three modalities and their complex interactions of spoken text, visual and vocal features.	Complexity
S. Sahay et al. [23] Proceedings of Grand Challenge and Workshop on Human Multimodal Language (Challenge-HML)-2018	Understanding Affect from video	Multi-modal relational tensor network for sentiment and emotion classification	language, audio and video domains fuse in multi-modal techniques to fuse the modalities	Treat the segments of a video independently.

Author(s)	Key work	Methodology	Performance Results	Limitations
M. M. Hassan et al. [27] Information Fusion, vol. 10.1016/j.inffus. 2018.10.009. 51, pp. 10–18,2019	Human emotion recognition	Deep belief network (DBN) architecture	DBN for depth level feature extraction from fused observations of EDA, PPG and zEMG sensors statistical features to prepare a feature-fusion vector for classification	Classification of Happy, Relaxed, Disgust, Sad, Neutral expression Sensor based operating complexity
J. Njoku et al. [29] The Journal of Korean Institute of Communications and Information Sciences, vol. 47, no. 1, pp. 79–87, Jan. 2022	Deep Learning Based Data Fusion Methods for Multimodal Emotion Recognition	Advanced Deep-learning to identify emotions	Visual, Vocal and physiological EEG signals data fusion at early, late, hybrid fusion.	Create an emotional profile avoiding noise and natural ambiguity of human expressions Complex operating (EEG) for detection
Komal et al. [30] Reliability: Theory and Application “ISSN 1932-2321, Volume 17 Issue 1 PP-67 March 2022 SCOPUS	Effect Of Prepossessing in Human Emotion Analysis Using Social Media Status Data set	Social media status dataset is first pre-processed using various methods, given for feature extraction and classification purpose.	Machine learning approach, count vectors and TF-IDF techniques for extracting the different features	Complex operating for detection
Shanliang Yang et al. [41] Science Direct 2024	Enhancing multimodal depression diagnosis through representation learning and knowledge transfer	Multimodal fusion visual, audio, text signals and Knowledge transfer from pretrained language models (SentiLARE)and multimodal emotion datasets (CMU-MOSEI)	Auto encoder-based representation learning with BiLSTM encoders/ encoders/decoders and fused feature for final classification. conditions	Integration of findings from longitudinal and epidemiological studies provides bidirectional relationship between depression and chronic health

2.6 Major Domain Related Challenges:

- 1) Psychology versus Computer Science: Psychology domain and Computer science domain have their specific specialty, complexity and dependency.
- 2) Natural versus posed expression: There are major differences in actual and acted expressions make a large impact. The expression intensity, reality, reliability and movement of muscles at macro and micro expressions play a major difference in expression execution.
- 3) Expression versus Emotion: Expression is defined as movement of muscles while Emotions are related to heart and inner or deeper feelings than mind. Expression can fabricate or acted or false while emotions are pure and real.
- 4) Static versus Dynamic analysis: Static image processing is still image-based processing while dynamic or video-based analysis has number of frames which required large and complex processing.
- 5) Transitions among expressions and fusion expression: When expression transition occurs figured out any one expression is quite difficult and/or challenging and to separate expression uniquely from fusion expressions are quite challenging and complex task.
- 6) Subjective Variations facial expression intensity level: The intensity difference between expressions is subjective based on number of parameters like age, race, sex and ethnicity so take a decision globally is quite challenging and complex.
- 7) Deliberate versus spontaneous expression: In many time executions of spontaneous expression varies large from deliberate expression in various aspects.
- 8) Head orientation and scene complexity: Head is prime region where expression execution happens so extract Region of Interest (ROI) reduced the computational complexity, cost and burden
- 9) Neural Network limitations: To train and execute Neural Network model we required quality and quantity of data which is always a big challenge.
- 10) Spatial temporal setting during data collection: as in Image and/or video processing spatial temporal data have a crucial role and as it is very sensitive to light data collection in real time environment is a challenging and precise task so standard metrics and requirement of wild implementation play a crucial role for researcher.
- 11) Emotional classes versus data classes in data labeling: Mapping of emotions and

standard labeled data are big challenges.

- 12) Over fitting versus generalization: To maintain thin line between overfitting and generalization is a quite difficult for any Neural Network.
- 13) Diagnostic criteria, clinical instruments, and performance metrics which have wide variety globally.
- 14) Clinical specificity: as many psychiatric and medical disorders-occur parallel with depressive disorder so it's subjective aspects.
- 15) Temporal dynamics important in psycho motor retardation.
- 16) Diversified large samples of data having variety of cultures, ethnicities, ages, and genders etc. Are a great challenge.

2.7 Research Gaps:

Non availability of user friendly, real-time, multimodal depression detection tool.

- 1) Negligence of mental health – care: Quality and quantity of mental health care service provider
- 2) Social stigma: Person with mental health issues not accept the ground truth and not ready to seek professional help
- 3) User friendliness approach for detection: In Current scenario though various approaches for depression detection exists user-friendliness is major concern.
- 4) Key challenges include limited labeled data, high complex sensor-based methodology for depression detection.

2.8 Definition of the Problem Statement

“To prepare real-time mood monitoring and prediction tool which can further classify person’s present mood in positive and negative mood from behavior analysis”

The increasing issues related to mental health highly demand real-time, automated systems that can accurately detect depression in user friendly manner.

2.9 Research Objectives and Scope of Work

Objectives: The main objective of the research is to design and implement real time, Multi Modal User Responsive tool for depression detection for said task we have selected three

modalities called Visual features, Self Response Inventory and colour psychology

To achieve this, the study is guided by the specific objectives:

Objective 1: Drive deeper into existing depression detection system.

Objective 2: Develop a user-friendly real-time multimodal depression detection system.

Objective 3: To validate the proposed method through performance parameters.

Objective 4: Apply the tool in wild conditions to confirm its compatibility, reliability and effectiveness.

Objective 5: Validate Automatic mood detection tool: Self Response Inventory

To detect Depression or depressive disorder person behavior analysis is required to carry out for that from existing approaches we have selected three simple and user-friendly options called Visual features from (static picture and/or video), Self Response Inventory (S.R.I) in which unique questionnaire related to physical and mental health related questions along with colour psychology are asked and if they are correctly responded we can judge the mood of person.

Scope of work:

1. Design a user-friendly depression detection system.
2. Develop a real-time mood monitoring and prediction tool which can further classify person's present mood in positive and negative mood based on behavior analysis.
3. Validate such tool on performance matrix and parameters.
4. Validate such tool in real time wild conditions.
5. Apply the tool in wild conditions to confirm its compatibility, reliability and effectiveness.

CHAPTER–3

Approaches for Depression Detection

3.1 Introduction:

Existing approaches for depression detection majorly listed as

- (1) Clinical Approach
- (2) Behavioral Approach
- (3) Psychological Approach
- (4) Social media Approach
- (5) Bio sensor instrument related Approach
- (6) Multimodal Approach

From above all we have selected first approach as Questionnaires approach in which details questions related to physical and mental health of a person along with colour selections decide the mood of the person and based on responses or score person mental health is decided.

Second approach is of Facial Visual feature-based approach in which based on the facial expression of the person person's expressions and from that emotions or mood is decided so detailed literature study of these approaches is as below.

Third approach is psychological approach the major concerned regarding psychological questions are asked in above Questionnaires approach but Colour Psychology which is uncovered domain is identified for emotion/mood detection in which it is identified that people commonly associate certain colors with specific emotions so from selection of colour decide the psychology or mindset of person or mood of the person. We have selected two colors red and black which represent positive and negative emotions significantly thus fusion of above three approaches makes our proposed approach.

3.2 Visual Features Base Approach:

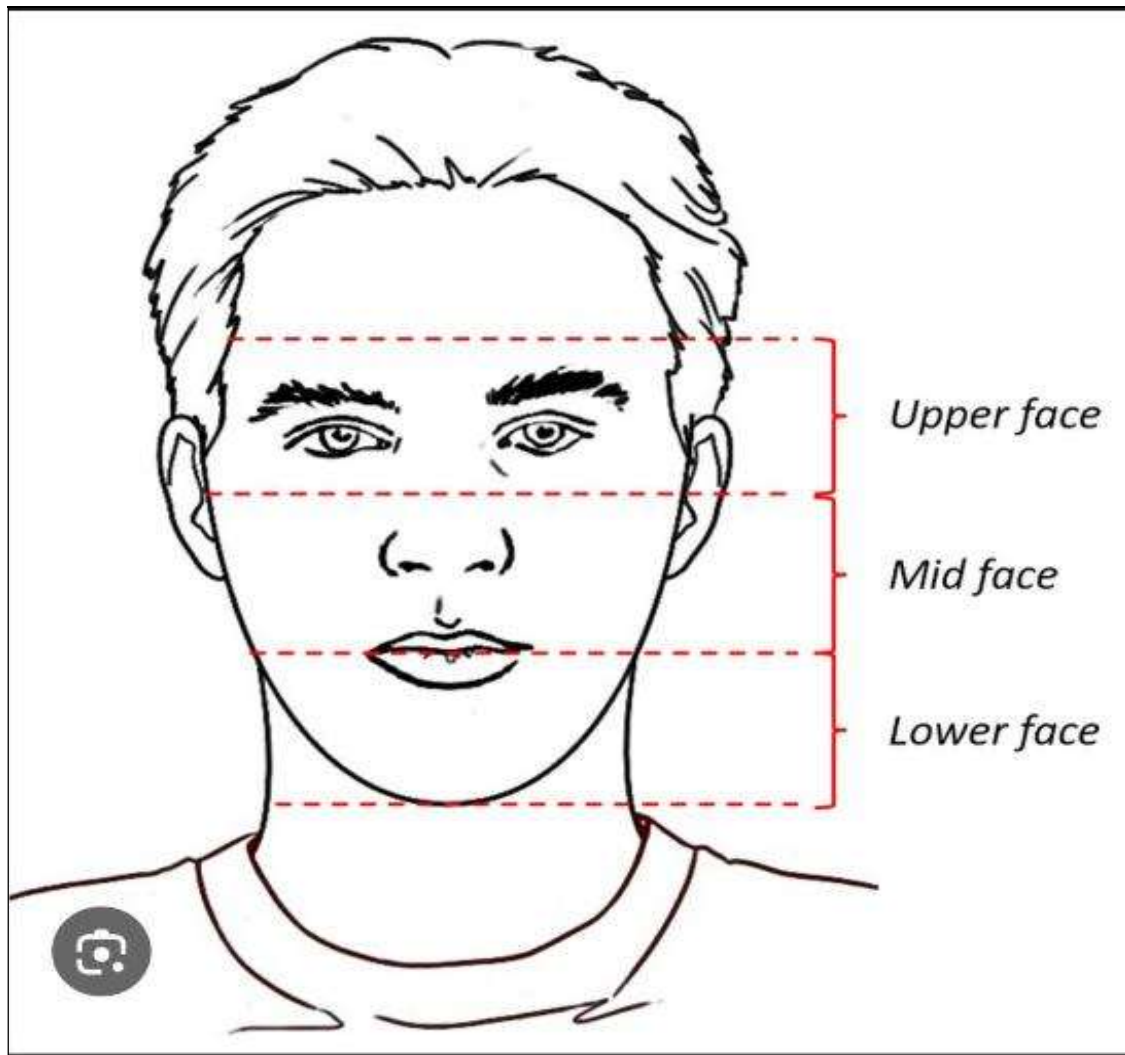


Figure 3.1: Illustration of Face Segment [55]

Face is the prime part of our body system to reflect expression and/or emotions. Figure 3.1 shows how Face is divided into main three parts Upper, middle and lower part. Eyebrows, Eyes are in upper part of face. Nose, cheeks and Ears are in middle part in which ears and nose are mainly static parts related to expressions, while cheek's movements are changed with expressions. In lower part of face lips, upper lips portion and chin are major and based on the expression the lip and surrounding its muscles movements are important for facial expression recognition. Major features related to face region are listed in Table 3.1

Table 3.1: List of major Visual Features for Behavior Detection

Features	Association with Facial Features
1	Eyelid opening / squinting movement
2	Outward appearance event with inconstancy with force
3	Head appearance with direction and deployment
4	Face movement
5	Pupil enlargement / inclination
6	Iris development
7	Grin force and term
8	Eye stare
9	Dismissal articulation/negative event
10	Mouth corner appearance

Action Units (AUs) defines various movement of individual facial muscles as defined by Facial Action Coding System (FACS) by Ekman et al. [48]. Facial Action Coding System (FACS) correlate Action Units with corresponding facial expression shown in Table 3.2 and Table 3.3 Identify Major Action Unit with expressions.

Table 3.2: Action Units (AUs) mapping with Expression

Action Units	Expressions
Brows	
AU 1+2	Inner and Outer portions of the brows are raised
AU 1+4	Medial portion of the eyebrows is raised and pulled together
AU4	Brows are lowered and pulled together
Eyes	
AU5	Upper eyelids are raised make eyes wider
AU6	Lower eyes and infra-orbital furrows are raised, deepened and make narrow eye opening
AU7	Lower eyelids are tightened make narrow eye opening
Mouth	
AU 27	Mouth is stretched open and extended
AU 26	Lips are relaxed and parted not lowered
AU 12+25	AU 12 with open mouth
AU 25	Lips are relaxed and parted not lowered
AU 20+25	Lips are parted, pulled back laterally may be slight raised or pulled

Table 3.3: Identification Major Action Unit (AU) to Expressions mapping

Action Unit (AU)	Expressions	Action Unit (AU)	Expressions
AU 1	Fear, Sad, Surprise	AU 14	Contempt
AU 4	Fear, Sad, Anger	AU 15	Sad
AU 6	Happy	AU 17	Sad
AU 10	Disgust	AU 24	Anger
AU 12	Happy		

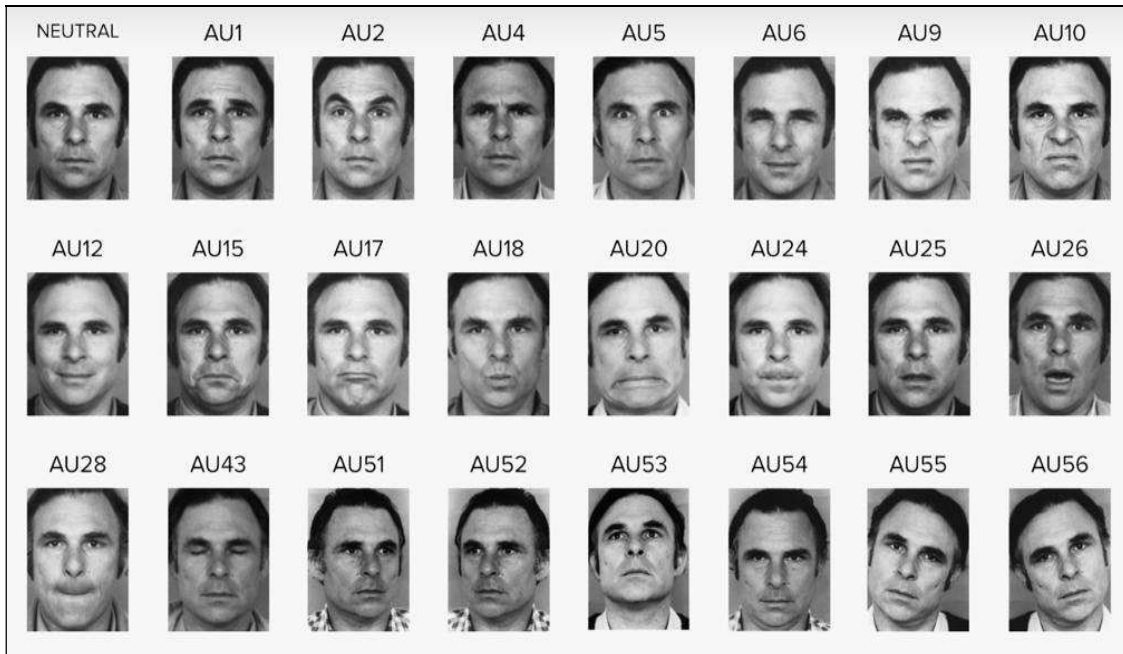
**FIGURE 3.2: Displays of Various Action Units (AUs) [56]**

Figure 3.2 display various Action Units presented for identifications purpose. FER is mainly conducted using images or videos containing facial emotional cues. Deep learning-based FER can greatly reduce the dependence on the handcraft-feature design by constructing an end-to-end feature representation directly from input images. The main goal of training DL-based FER is to overcome over fitting when using relatively small facial expression databases, as well as to improve accuracy. As shown in Figure 3.3, FER2013 dataset is first read pixel wise then various pre- processing techniques are applied, then

splitting it into training and testing labels into categorical ones, converting pixels into NumPy array and reshaping the data are applied. This pre-processed dataset is given to the Deep CNN model. The model is trained and achieved 68% accuracy and its performance parameter presented in Table 3.4.

Figure 3.4 represent corresponding confusion matrix and Figure 3.5 represent Graphical representation of accuracy and loss measure for facial emotion recognition.

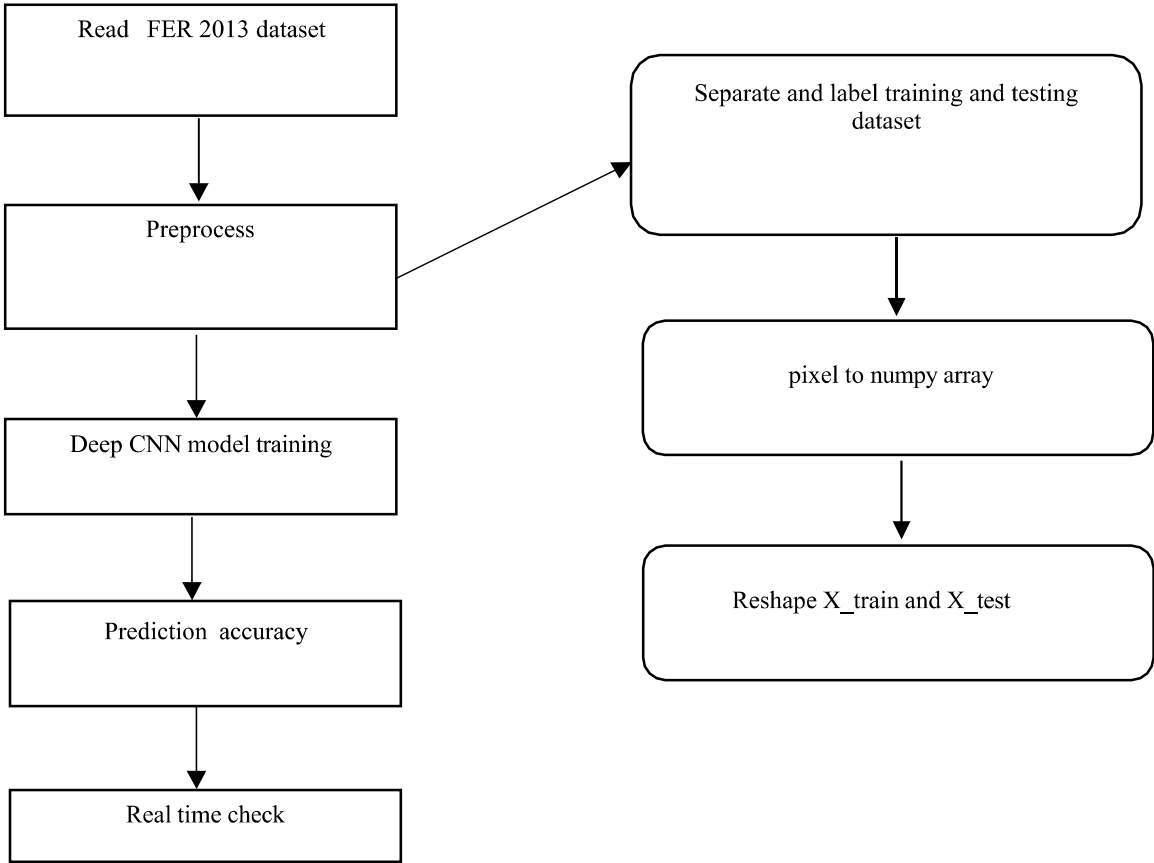


FIGURE 3.3: Flow Chart of Visual Feature Base Approach

TABLE 3.4: Class-wise precision, recall, F1- score and support of FER

Type of Emotion	Precision	Recall	F1-score	Support
Angry	0.532	0.586	0.556	958
Disgust	0.969	0.63	0.764	111
Fear	0.515	0.52	0.517	1024
Happy	0.727	0.86	0.79	1774
Sad	0.518	0.59	0.552	1247
Surprise	0.820	0.73	0.772	831
Neutral	0.602	0.62	0.611	1232

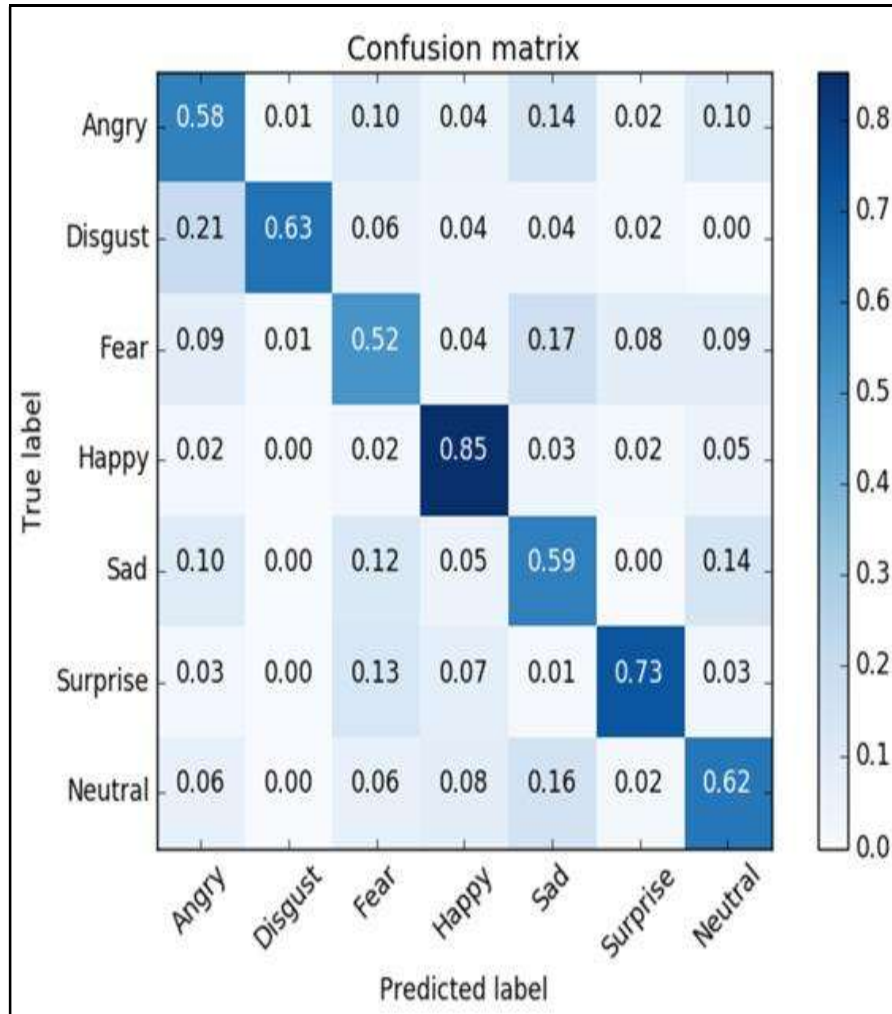


FIGURE 3.4: Confusion Matrix for Visual Feature Based Approach

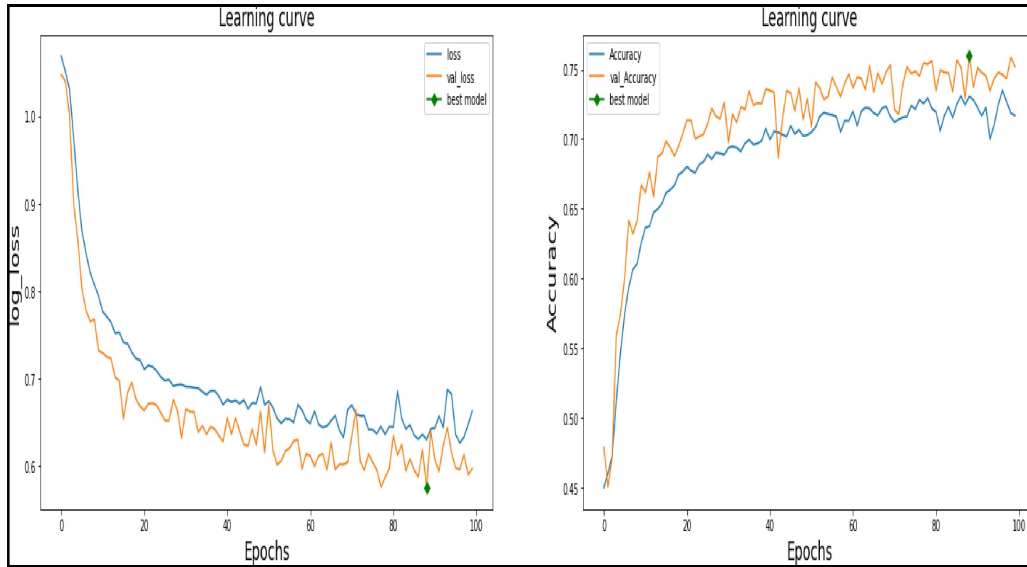


FIGURE 3.5: Accuracy and loss measures for Visual Feature Based Approach

3.3 Self-Response Inventory (S.R.I.) Base Approach

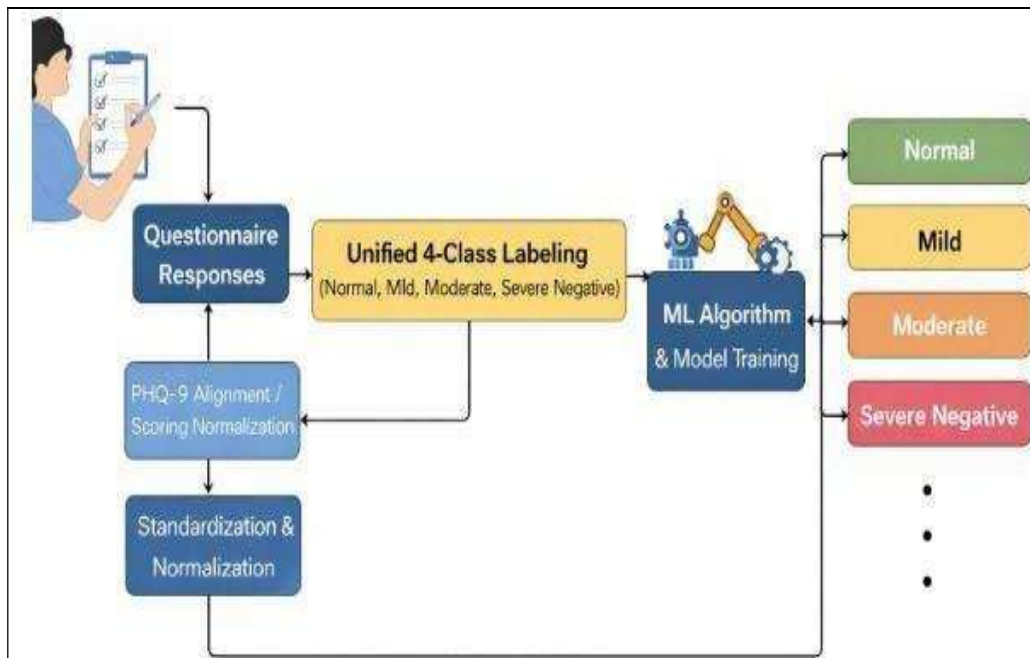


FIGURE 3.6: Machine learning model for S.R.I.

Figure 3.6 Machine learning approach for Self-Response Inventory (S.R.I.) in which based on the response person is classified in four class called Normal, Mild, Moderate or Severe negative mood.

Table 3.5 represent S.R.I. of 21 questions related to behavior pattern of person for screening purpose which mainly decide food, sleep, routine, mental and physical activities related questionnaires to identify mood of the person.

TABLE 3.5: Self Response Inventory (S.R.I.)

Sr no	Question (Select option based on past 2-3 days experience)	Outcome	Yes	No	Not Decided
1	Have you taken enough sleep?	Rest			
	Evaluates your physical well-being and rest. Adequate sleep is essential for health and productivity.				
2	Have you taken enough healthy food (in bf / lunch /dinner)?	Food			
	Assesses whether you're meeting your nutritional needs for energy and overall health.				
3	Have you done any exercise/yoga/workout?	Exercise			
	Reflects your physical activity levels, which are important for maintaining health, fitness, and mental well-being.				
4	Are you enjoying your daily routine?	Enjoyment			
	Indicates satisfaction and contentment with your daily life and habits.				
5	Can you select your clothes by yourself?	Decision			
	Measures independence and autonomy in decision-making and self-care.				
6	Can you prepare / suggest foods? (For breakfast / lunch /dinner)?	Selection/Creativity			
	Evaluates self-sufficiency in meal planning and preparation.				
7	Have you interacted with your family members to share your thoughts or feelings?	Sharing feelings			
	Assesses emotional connectivity and communication with loved ones.				
8	Are you comfortable to communicate with your neighbors / colleges or friends?	Communication			
	Measures your social comfort and ability to engage with people in various settings.				
9	Do you spare some time to do your liking things?	Hobby /liking			
	Reflects your balance between responsibilities and personal enjoyment or hobbies.				
10	Can you read newspaper/books/articles easily?	Concentration			
	Evaluates cognitive function, literacy, and engagement with information.				
11	Can you watch TV/mobile/Movie easily?	Concentration			

Sr no	Question (Select option based on past 2-3 days experience)	Outcome	Yes	No	Not Decided
	Measures ease of leisure activity and mental relaxation.				
12	Are you satisfied with your individual achievement/contribution to family/Society?	Self-esteem			
	Reflects self-assessment of your accomplishments and your sense of purpose and fulfillment of your efforts and knowledge/Skills and attitude.				
13	Do you have interest in things which appeal you a lot previously?	Active Participation			
	Examines personal interests and desires related to romantic/pleasure connections.				
14	Do you feel your life going smoothly?	Satisfaction			
	Reflects your perception of life's trajectory and personal well-being.				
15	Do you feel tomorrow is better than present?	Optimistic			
	Indicates optimism and hope for the better future.				
16	Do you feel you are unique and no one can replace yourself?	Self-esteem			
	Reflects self-worth and a sense of individuality.				
17	Do you feel stress of your study/work /responsibilities?	Stress			
	Whether you experience feelings of pressure, anxiety, or overwhelm due to your academic, professional, or personal duties.				
18	Do you feel nothing going on track and after a lot of efforts from your side u can't do anything?	Out of control situation			
	if you ever feel like, despite putting in a lot of hard work and effort, things still aren't progressing as they should. It reflects a sense of frustration or helplessness,				
19	Do you feel frustrated or aloneness?	Helplessness			
	Reflects feelings of frustration, helplessness, or burnout. The outcome of this question could reveal several underlying emotional or psychological states, such as: Frustration or Disappointment, Helplessness or Powerlessness, Burnout, Lack of Progress or Direction, Self-Doubt.				
20	Selection of Colour base on your mood from these: Black/Red/None	Colour			
	Mood association with colour.				
21	Have you come across with negative thoughts /suicidal thoughts?	Negative			
	Negativity				

3.4 Colour Psychology Base Approach

Colour based Emotions association		
Colour	Percentage	Emotions
BLACK	51 %	Sad (-)
White	43 %	Relief
Red	68 %	Love(+)
Blue	35 %	Relief
Green	39 %	Contentment(-)
Yellow	52 %	Joy(+)
Purple	25 %	Pleasant(+)
Brown	36 %	Disgust(-)
Orange	44 %	Joy (+)
Pink	50 %	Love (+)

FIGURE 3.7 Colour association with Emotions

As shown in Figure 3.7 we selected two colours with maximum probability with emotions association. Red colour representing positive emotion (love) with 68% and Black colour to identified negative mood or sad emotion with 51%. So based on selection from either black or Red colour we can decide the emotion or mood of the person as negative or positive. If no colour selection is selected we neutralized the mood neither positive nor negative.

3.5 Summary and Conclusion

This thesis mainly focus on depression detection through multimodal approach in simple, user-friendly manner. The proposed model process facial expression, Self Response Inventory and colour psychology-based emotion recognition for emotions, mood detection and based on that prediction of depressive disorder or depression.

CHAPTER–4

Proposed Multimodal Approach for User Responsive Depression Detection

4.1 Proposed Approach and Methodology:

We have decided to use three approaches for Depression Detection

- (1) Visual features-based approach in which from through static picture and / Or video the emotions or mood of the person is decided
- (2) Self Response Inventory (S.R.I.) a unique questionnaire method for mood detection
- (3) Colour psychology-based approach in which from colour selection of person emotions and/ or mood is decided in above

Depending on results of above modalities we can decide emotions / mood of a person either positive or negative and if person remains more than 2 weeks continuously in negative state of mind person may converge to Depressive disorder.

(1) Visual as major channel for Depression detection:

Face is the strong channel of emotions indication. People reflect their feelings knowingly or unknowingly by their facial expression so face is considered as prime part of body for expression so based on this fact Ekman et al. [4] categorize standard expression of six fundamental feelings. Wagner et al. [9] relate head orientation, posture and movement majorly use to recognize depression. Girard et al. [10] explore strong co-relation between visual direction and depression and confirmed nonverbal social withdrawal in depression.

This research develops a depression detection system as shown in Figure 4.1 which incorporates data inputs from image, video (stored and live) for visual

feature-based assessment. Data acquisition, data processing, system construction, and model performance evaluation are described as follows.

Model take visual input data from camera for static picture in stored and real-time manner and also same from video same processing that is real-time and stored file video upload options for testing is also available based on visual feature analysis the person's emotions are identified.

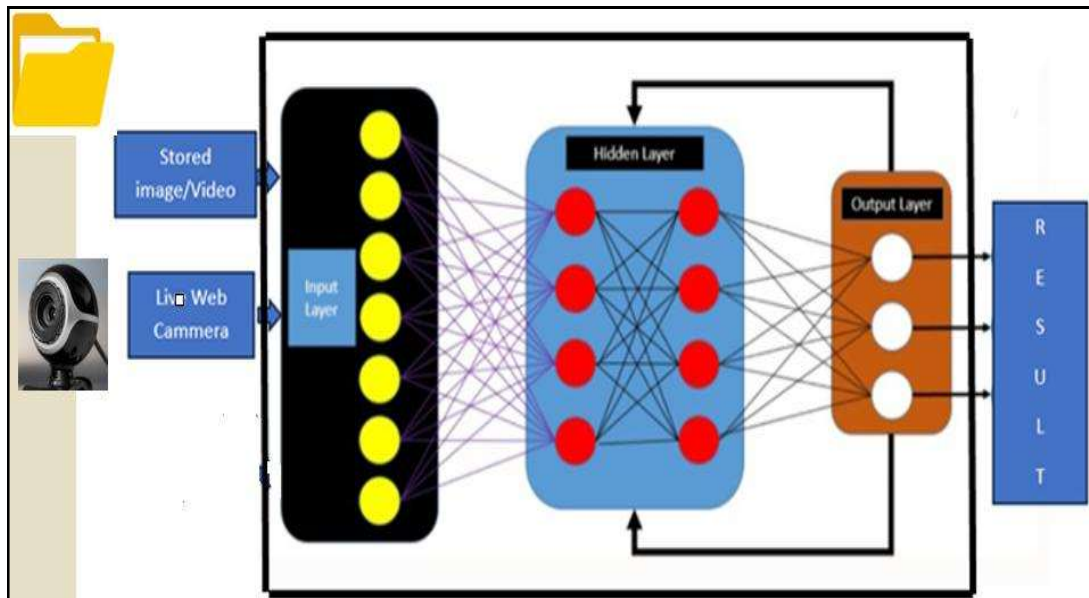


Figure 4.1: Depression detection Deep Neural Network model

Model Architecture:

Deep Learning model of CNN (Convolution Neural Network) is used for creating, training and analyze expression from static image and video channel major components of architecture are as below:

- (1) Convolution Layers (4): Multiple Convolution layers to extract features from images using multiple filters (32, 64, 128, and 256) of kernel sizes (3 x 3) which extract features from images.
- (2) Rectified Linear Unit (ReLU): function used for non-linearity introduction.
- (3) Max Pooling layers (3): perform reduction of spatial dimension reduction so computational complexity also reduced.
- (4) Dropout (3): Layer drops randomly some nodes in training phase so model does not have tendency of Over fitting.

- (5) Flatten Layer (1): Converts the 2D feature maps into a 1D vector for input to dense layers.
- (6) Dense Layers (2): These are fully connected layers for seven expressions classifications

Above layers include Image Pre-processing, Data Augmentation, data generation, training and Validation total 13-layers present in architecture.

Activation Functions: ReLU, Softmax

Output Classes: Angry, Disgust, Fear, Happy, Neutral, Sad, Surprise (7 class). Detailed description of Deep CNN architecture is presented in Table 4.1.

Table 4.1: Detailed Description of Deep CNN architecture

Sr.	Layer	Description	Configuration	Functionality
1	Conv2D	32 filters	3 x 3, ReLU	Extracts edges, texture like basic features
2	Conv2D	64 filters	3 x 3, ReLU	Learn more complex facial patterns
3	MaxPooling2D	Pooling layer	2 x 2 pool size	Reduce image size and computation
4	Dropout	Prevent Overfitting	0.1	By randomly disabling neurons prevent overfitting
5	Conv2D	128 filters	3 x 3, ReLU	Detect higher level facial features
6	MaxPooling2D	Pooling layer	2 x 2 pool size	Down samples feature maps
7	Dropout	Prevent Overfitting	0.1	Improves model generalization
8	Conv2D	256 filters	3 x 3, ReLU	Learns deep emotion related features
9	MaxPooling2D	Pooling layer	2 x 2 pool size	Further reduce dimensions
10	Dropout	Prevent Overfitting	0.1	Reduce overfitting risk
11	Flatten	Converts 2D to 1D		Converts 2D feature maps into 1Dvector
12	Dense	512 neurons	512 neurons, ReLU	Perform High-level learning and Classification
13	Dense	Output layer of 7 classes	Output layer (7 classes)	Predict Probability of 7 emotions: Angry, Disgust, Fear, Happy, Neutral, Sad, Surprise

4.2 Datasets Design and Acquisition:

The FER2013 is open dataset (Facial Expression Recognition 2013) [44] which consist of facial images along with their emotion categories of person. The database has facial images of size 48×48 pixels of monochrome images with seven different categories of emotions Angry, Disgust, Fear, Happy, Sad, Surprise, and Neutral. The dataset having 28709 images in the training set and 3589 images in testing set.

Data acquisition:

Depression detection model obtained data from three sources which are static/dynamic images capture from camera both live and stored and quiz responses.

Data channel -1: Input image from Camera in real time video:

Images and / or Video from camera are captured and continuously images are identified in categorical expressions based on that positive and negative expressions can be determined. Happy expression is considered as positive bias images where Sad, Fear, Angry, and Disgust are negative biased images. Neutral and Surprise have no bias.

Data channel -2: Stored image and video:

From Stored Image and / or Video images are identified in categorical expressions and then positive and negative expression images are identified.

(2) Self-Response Inventory (S.R.I.) a unique questionnaire for mood detection:

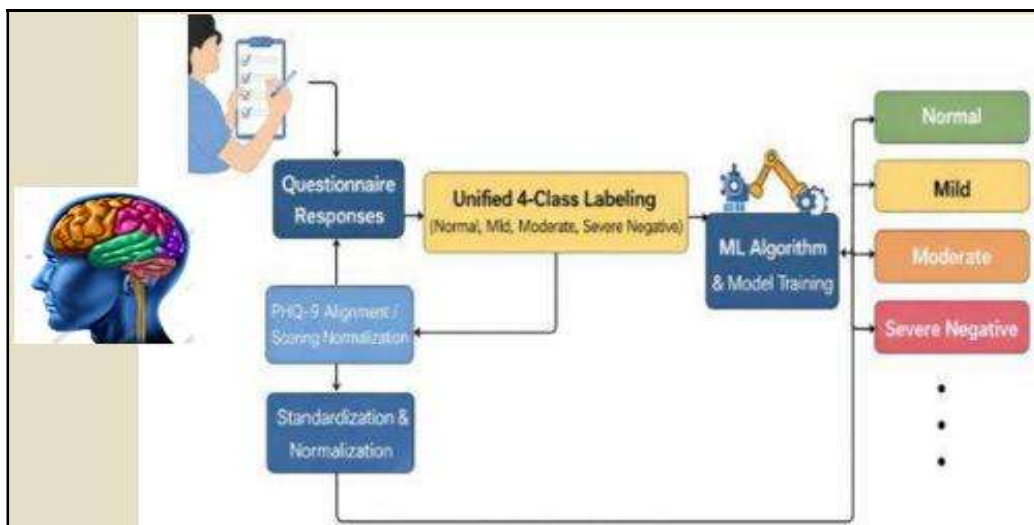


Figure 4.2: Proposed Self Response Inventory (S.R.I.)

As shown in Figure (4.2) S.R.I. module based on Machine Learning algorithm classified in four class called Normal, Mild, Moderate and Severe negative mood.

Table 4.2 represent S.R.I. which consist of 21 questions related to behavior pattern of person for screening purpose which mainly decide food, sleep, routine, mental and physical health activities related questionnaires to identify mood of the person based on past 2-3 days experience. Total 150 responses collected and their statistical analysis is presented in this chapter.

Table 4.2: Proposed Self Response Inventory (S.R.I.)

Sr no	Question (Select option based on past 2-3 days experience)	Outcome	Yes	No	Not Decided
1	Have you taken enough sleep?	Sound Sleep / Rest	0	1	0
	Evaluates your physical well-being and rest. Adequate sleep is essential for health and productivity.				
2	Have you taken enough healthy food (in bf / lunch /dinner)?	Healthy Food	0	1	0
	Assesses whether you're meeting your nutritional needs for energy and overall health.				
3	Have you done any exercise/yoga/workout?	Exercise	0	1	0
	Reflects your physical activity levels, which are important for maintaining health, fitness, and mental well-being.				
4	Are you enjoying your daily routine?	Enjoyment in Daily routine	0	1	0
	Indicates satisfaction and contentment with your daily life and habits.				
5	Can you select your clothes by yourself?	Decision making	0	1	0
	Measures independence and autonomy in decision-making and self-care.				
6	Can you prepare / suggest foods? (For breakfast / lunch /dinner)?	Selection /Creativity	0	1	0
	Evaluates self-sufficiency in meal planning and preparation.				
7	Have you interacted with your family members to share your thoughts or feelings?	Sharing feelings	0	1	0
	Assesses emotional connectivity and communication with loved ones.				
8	Are you comfortable to communicate with your neighbors / colleges or friends?	Communication	0	1	0

Sr no	Question (Select option based on past 2-3 days experience)	Outcome	Yes	No	Not Decided
	Measures your social comfort and ability to engage with people in various settings.				
9	Do you spare some time to do your liking things?	Hobby or activities of liking things	0	1	0
	Reflects your balance between responsibilities and personal enjoyment or hobbies.				
10	Can you read newspaper / books / articles easily?	Concentration in reading (Eye and mind co-ordination)	0	1	0
	Evaluates cognitive function, literacy, and engagement with information.				
11	Can you watch TV/mobile/Movie easily?	Concentration in watching and listening (Ear, Eyes and mind co-ordinations)	0	1	0
	Measures ease of leisure activity and mental relaxation.				
12	Are you satisfied with your individual achievement / contribution to family/Society?	Self-esteem	0	1	0
	Reflects self-assessment of your accomplishments and your sense of purpose and fulfillment of your efforts and knowledge/Skills and attitude.				
13	Do you have interest in things which appeal you a lot previously?	Active Participation	0	1	0
	Examines personal interests and desires related to romantic/pleasure connections.				
14	Do you feel your life going smoothly?	Smooth going life with Satisfaction	0	1	0
	Reflects your perception of life's trajectory and personal well-being.				
15	Do you feel tomorrow is better than present?	Optimistic/hopeful	0	1	0
	Indicates optimism and hope for the better future.				
16	Do you feel you are unique and no one can replace yourself?	Self-esteem/ Uniqueness /Importance of own self	0	1	0
	Reflects self-worth and a sense of individuality.				
17	Do you feel stress of your study/work /responsibilities?	Stress	1	0	0
	Whether you experience feelings of pressure, anxiety, or overwhelm due to your academic, professional, or personal duties.				
18	Do you feel nothing going on track and after a lot of efforts from your	Out of control	1	0	0

Sr no	Question (Select option based on past 2-3 days experience)	Outcome	Yes	No	Not Decided
	side u can't do anything?	situation			
	if you ever feel like, despite putting in a lot of hard work and effort, things still aren't progressing as they should. It reflects a sense of frustration or helplessness,				
19	Do you feel frustrated or aloneness?	Helplessness	1	0	0
	Reflects feelings of frustration, helplessness, or burnout. The outcome of this question could reveal several underlying emotional or psychological states, such as: Frustration or Disappointment, Helplessness or Powerlessness, Burnout, Lack of Progress or Direction, Self-Doubt.				
20	Selection of Colour base on your mood from these: Black/Red/None	Colour Psychology Black:1, Red:0	1	0	0
	Mood association with colour.				
21	Have you come across with negative thoughts /suicidal thoughts?	Negative mindset	1	0	0
	Negativity				

Each response which converges to negative mood carry one (1) score. In remain two cases that is opposite case (positive mood) and “Not decided” selected as answer carry zero (0) score.

Scores obtained from responses - quiz score is converted from numeric to mood outcome label in classes as presented in Table 4.3 and outcome with corresponding suggestive actions are described in it.

Table 4.3: Classification of S.R.I. score

Sr no	Score range	Level	Mood Classification	Actions
1	0-4 points	Level 0	Normal	Just Calm...continue routine Stay healthy physically and mentally
2	5-8points	Level 1	Negative Mood	Repeat test, Take your mental health consciously
3	9-14 points	Level 2	Moderate Negative Mood	Repeat test, still result is same advisable to consult medical professional
4	more than 15 points	Level 3	Severe Negative Mood	Immediately consult medical professional

Table 4.4 present class-wise performance of proposed system of 150 person's with S.R.I. approach in Normal, Mild, Moderate and Severe Negative mood classification in confusion matrix form.

Table 4.4: Class-wise performance of proposed system

Class	Normal	Mild Negative	Moderate Negative	Severe Negative	Total
Normal	85	3	2	0	90
Mild-Neg.	4	29	2	0	35
Mod Neg.	1	2	14	1	18
Severe-Neg.	0	1	1	5	7
Total	90	35	19	6	150

Table 4.5 represent class wise performance of S.R.I. Based proposed system performance parameter in form of Precision, Recall and F1-score. Table 4.6 represent alignment of proposed S.R.I. based proposed system with clinically established method PHQ-9 which proved applicability of SRI approach.

Table 4.5: Class-wise performance of proposed system

Class	Precision	Recall	F1- Score
Normal	0.94	0.94	0.94
Mild-Negative	0.83	0.83	0.83
Moderate-Negative	0.74	0.78	0.76
Severe-Negative	0.83	0.71	0.77
Average	0.84	0.82	0.83

Table 4.6: Alignment of proposed system with PHQ-9

PHQ-9 range	Score Severity (PHQ-9)	Proposed System
0-4	Minimal	Normal Mood
5-9	Mild Depression	Mild Negative
10-14	Moderate Depression	Moderate Negative
Greater Than 15	Moderately Severe Depression	Severe Negative Mood

Figure 4.3 represent Precision-and Recall graph and pie chart for classification of S.R.I. Based Proposed system.

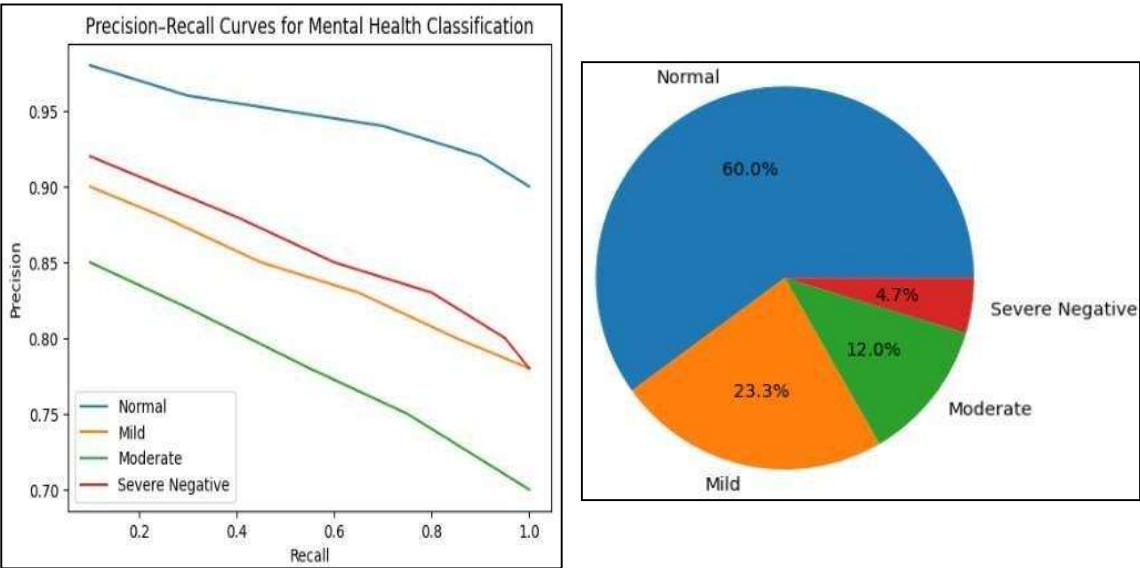
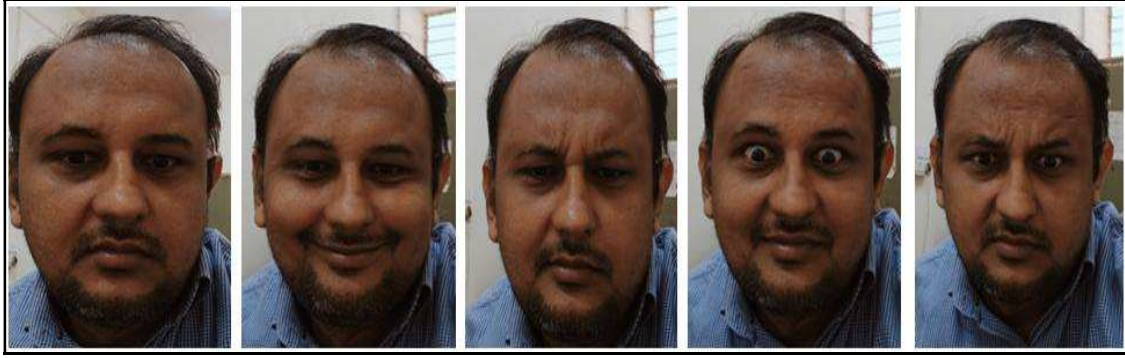


Figure 4.3: Precision-Recall graph and Pie chart for classification



Figure 4.4: Prototypic Facial Expression intra-class variability

Figure 4.4 represent prototypic Facial Expression intra-class variability of person.



**Figure 4.5: Testing Facial Expression intra class variability
(From Left to right Neutral, Happy, Contempt, Surprise and Disgust expressions)**



**Figure 4.6: Testing Facial Expression inter-class variability
(From Left to right Sad, Happy, Neutral, Happy and Contempt expressions)**

Figure 4.5 represent intra class variability of testing facial expressions while Figure 4.6 represent inter class variability. As shown in above figures face images are classified broadly into positive and negative groups. Happy is positive bias images where Sad, Fear, Angry and Disgust are negative biased images.

Neutral and Surprise have no biasing as per its name.

Figure 4.7 to 4.16 represent various testing results of expression by proposed system respectively and 4.17 represent confusion matrix of visual feature-based emotion recognition system.



Figure 4.7: Testing Result of Fear and Angry expression by Proposed System

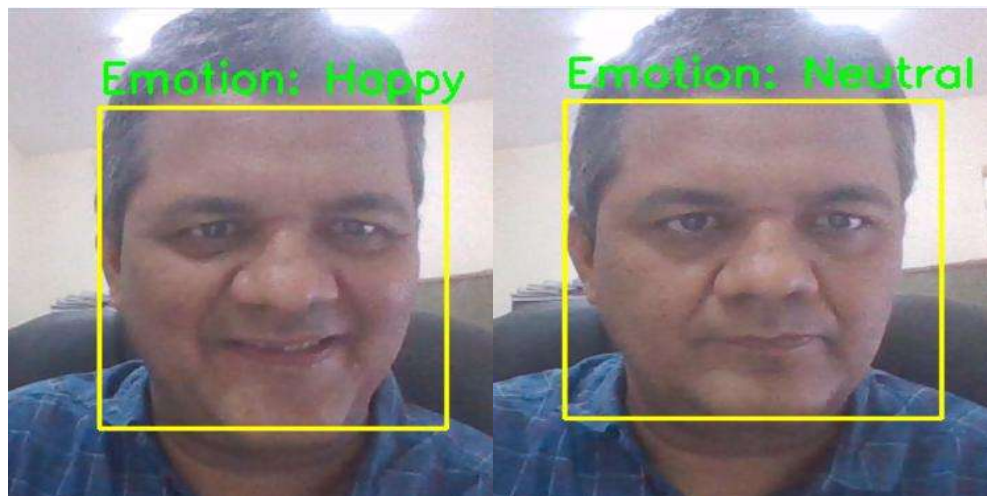


Figure4.8: Testing Result of Happy and Neutral expression by Proposed System



Figure 4.9: Testing Result of Sad and Surprise expression by Proposed System

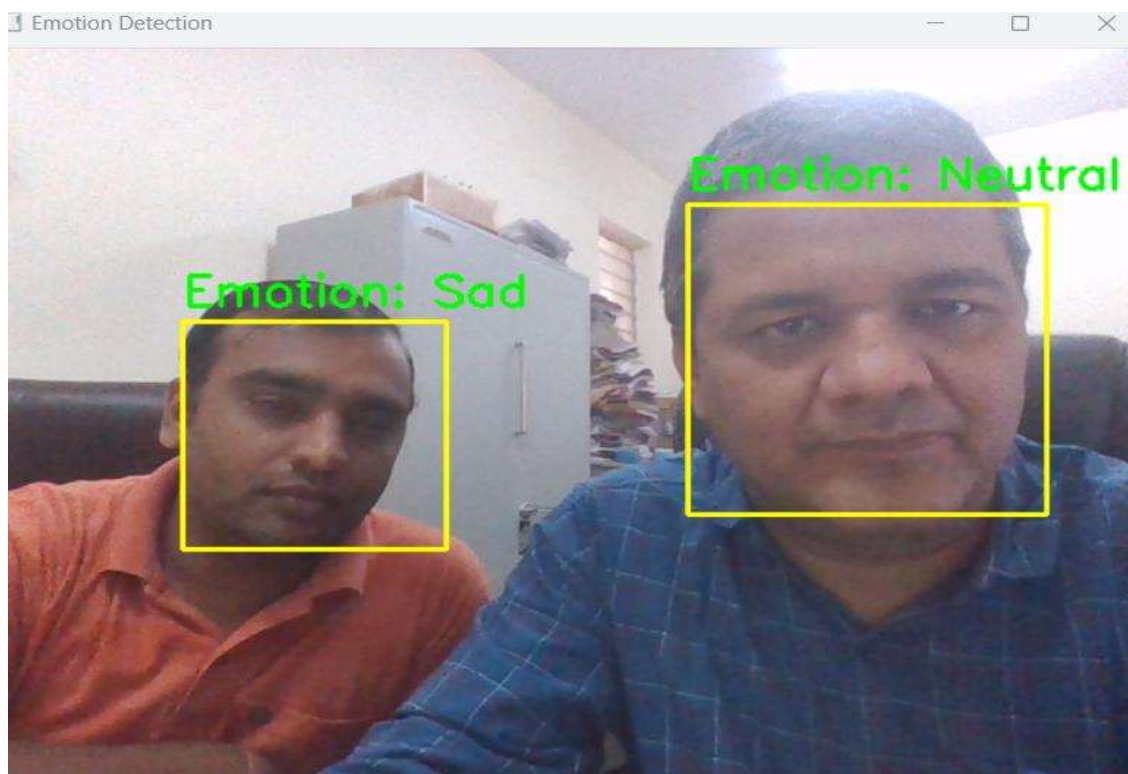


Figure 4.10: Testing Result of Sad and Neutral expression by Proposed System

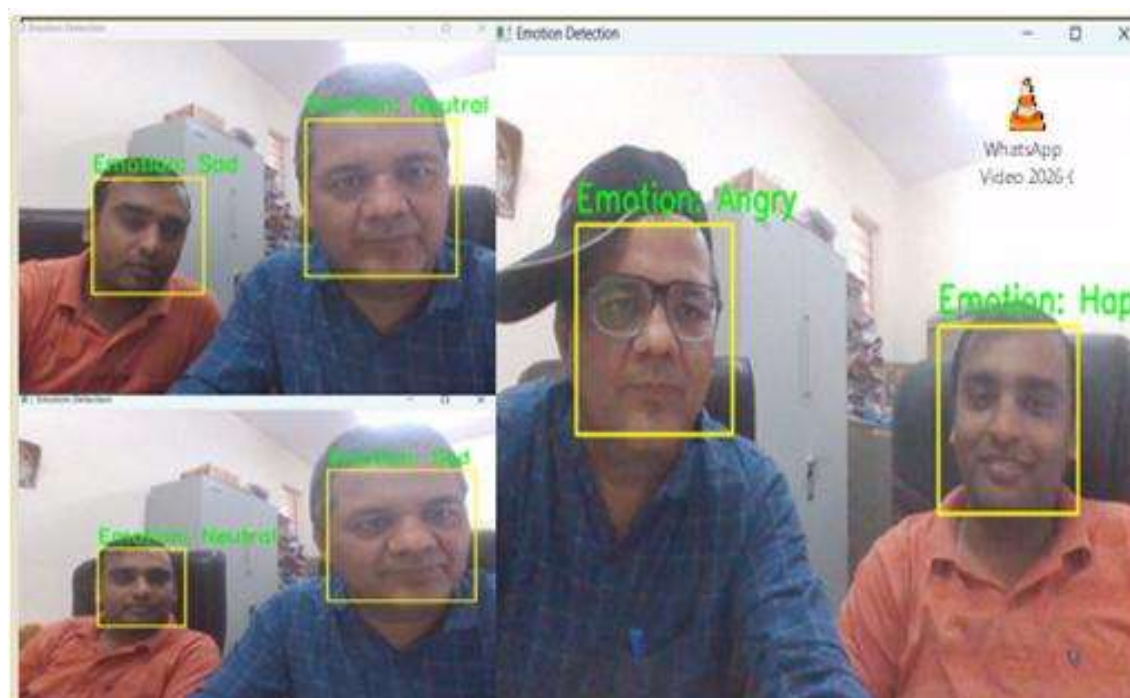


Figure 4.11: (from Left to Right)
Testing Result Sad and Neutral expression by Proposed System
Testing Result Neutral and Sad expression by Proposed System
Testing Result Angry and Happy expression by Proposed System



Figure 4.12: (from Left to Right)
Testing Result Sad and Neutral expression by Proposed System
Testing Result Angry and Neutral expression by Proposed System
Testing Result Happy expression by Proposed System



Figure 4.13: Testing Result of Sad and Happy expression by Proposed System

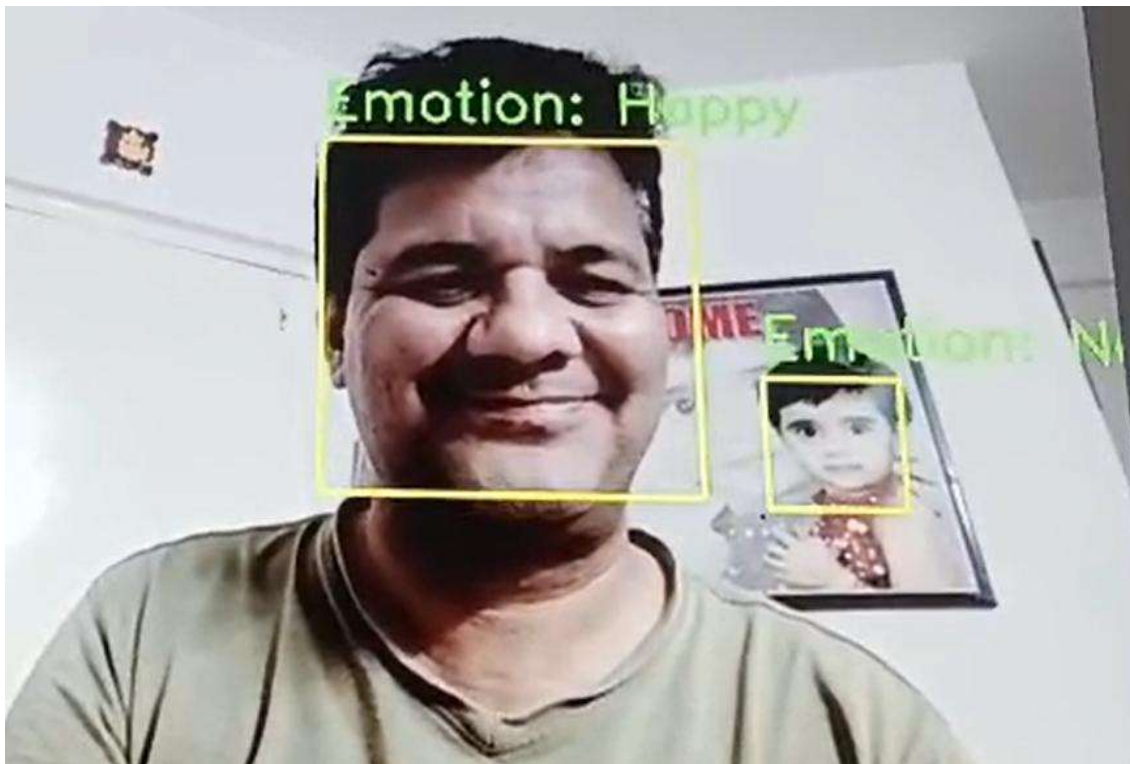


Figure 4.14: Testing Result of Happy and Neutral expression by Proposed System



Figure 4.15: Testing Result of Angry and Neutral expression by Proposed System

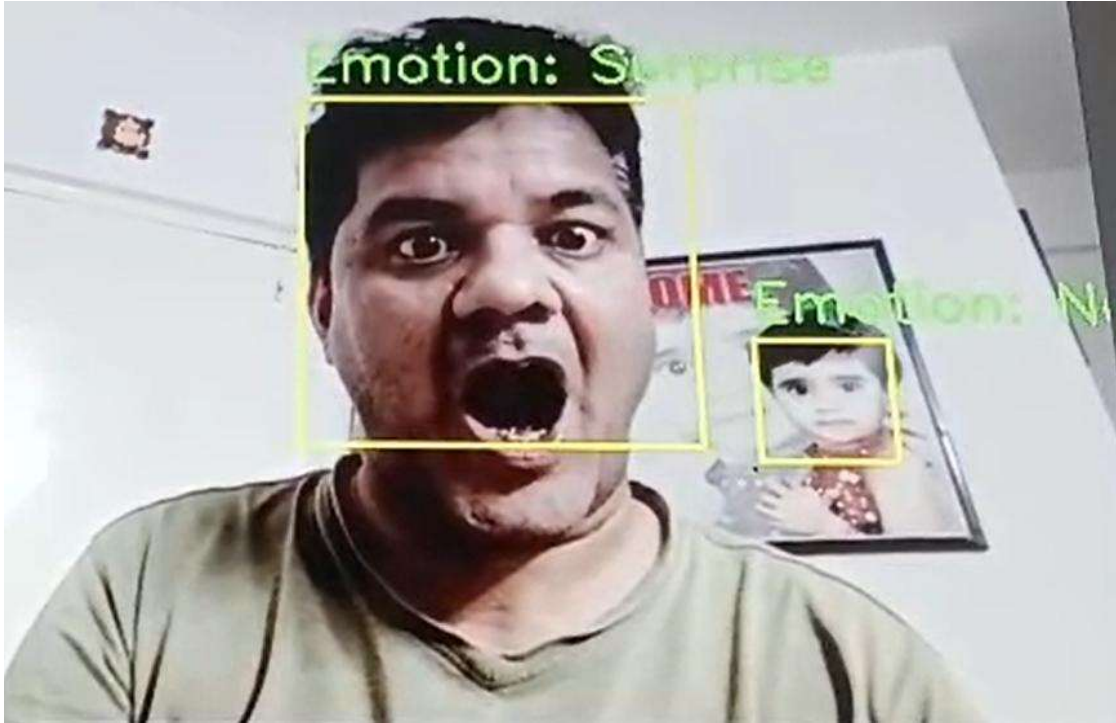


Figure 4.16: Testing Result of Surprise and Neutral expression by Proposed System

4.3 Results Analysis:

Table 4.7 present detailed numerical results of visual based emotion recognition proposed model performance.

Table 4.7: Model performance evaluation

(Epoch wise Training loss, Training accuracy, Validation loss and validation accuracy)

Epoch	Training Loss	Training Accuracy	Validation Loss	Validation Accuracy
1	2.2673	0.2043	2.0278	0.2493
2	1.8677	0.2697	1.6808	0.3757
3	1.6180	0.3736	1.6879	0.3589
4	1.4435	0.4470	1.2770	0.5007
5	1.3103	0.4982	1.2653	0.5237
6	1.2351	0.5255	1.2923	0.5056
7	1.2070	0.5357	1.2488	0.5189
8	1.1475	0.5628	1.0932	0.5803
9	1.1403	0.5671	1.1497	0.5628
10	1.0962	0.5850	1.0529	0.5992
11	1.0821	0.5887	1.0385	0.6027

Epoch	Training Loss	Training Accuracy	Validation Loss	Validation Accuracy
12	1.0651	0.5986	1.0442	0.5936
13	1.0482	0.6021	0.9976	0.6180
14	1.0344	0.6097	1.0922	0.6041
15	1.0152	0.6157	1.1200	0.5887
16	0.9960	0.6218	0.9868	0.6250
17	0.9973	0.6255	1.0060	0.6271
18	0.9561	0.6398	0.9771	0.6411
19	0.9605	0.6380	1.0074	0.6082
20	0.9468	0.6449	1.0069	0.6341
21	0.9391	0.6445	0.9674	0.6487
22	0.9247	0.6490	0.9729	0.6522
23	0.8960	0.6622	0.9405	0.6508
24	0.9082	0.6603	0.9881	0.6187
25	0.8918	0.6643	0.9616	0.6341
26	0.8988	0.6594	0.9764	0.6529
27	0.8824	0.6713	0.9893	0.6243
28	0.8660	0.6786	0.9972	0.6397
29	0.8636	0.6774	0.9671	0.6508
30	0.8598	0.6847	0.9640	0.6459
31	0.8403	0.6897	1.0170	0.6501
32	0.8273	0.6951	0.9798	0.6543
33	0.8183	0.6951	0.9737	0.6278
34	0.8195	0.6944	0.9706	0.6655
35	0.8011	0.6966	1.0212	0.6404
36	0.8174	0.6997	0.9421	0.6397
37	0.7934	0.7029	1.0191	0.6404
38	0.7851	0.7029	1.0593	0.6397
39	0.7841	0.7100	0.9531	0.6494
40	0.7779	0.7063	0.9565	0.6522
41	0.7669	0.7110	0.9169	0.6745
42	0.7594	0.7183	0.9593	0.6536
43	0.7406	0.7243	0.9267	0.6767
44	0.7310	0.7318	0.9420	0.6725
45	0.7191	0.7329	0.9537	0.6613

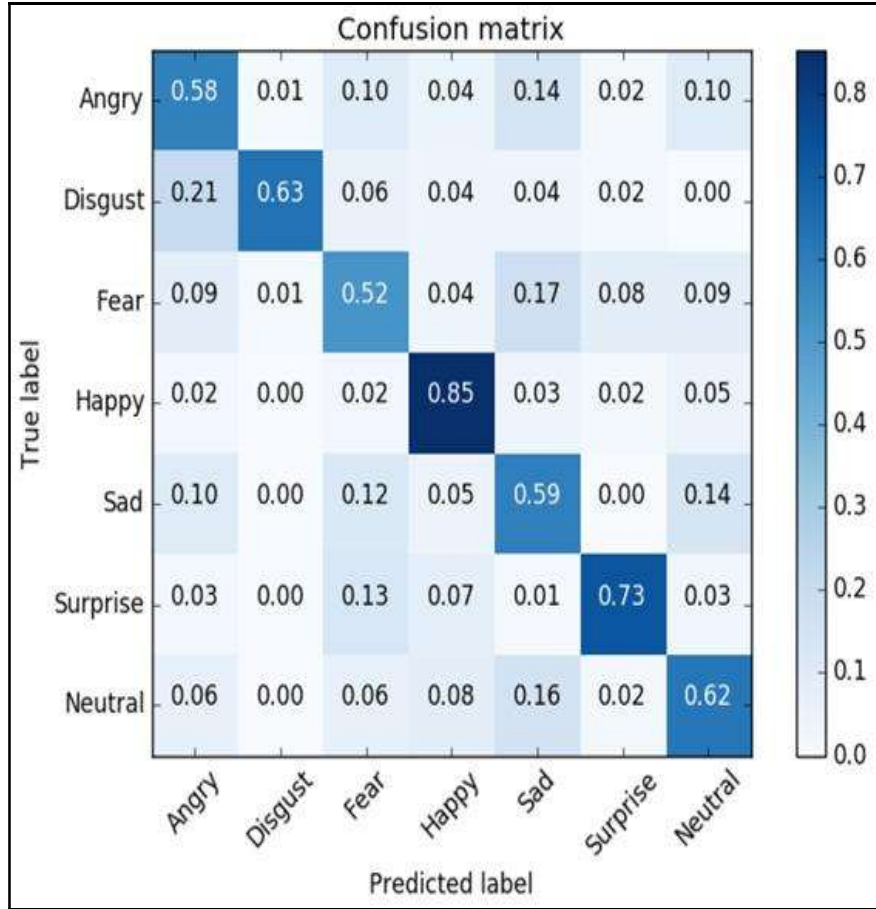


Figure 4.17: Confusion Matrix of Visual Feature Base Proposed System

Figure 4.17 represent confusion matrix of proposed visual feature-based system. True label (rows): The actual emotions present in the dataset (e.g., Angry, Disgust, etc.). Predicted label (columns): The emotions predicted by the classification model. Each cell contains the proportion of samples predicted for a given emotion compared to the true label.

4.4 Key observations:

Confusion matrix of model represents

- (a) Diagonal values 0.58 for angry, 0.85 for Happy represents correct predictions. Higher values along the diagonal indicate better performance for that specific emotion. The model predicts "Happy" correctly with 85% and "Neutral" correctly 62% of the time so remaining emotions are negative or converge to negative emotions.

- (b) Off-diagonal values: represent misclassifications where the model incorrectly predicts, a different emotion.eg. "Angry" is misclassified as "Fear" 10% of the time; "Neutral" is sometimes predicted as "Sad" (16%) etc.
- (c) Best and worst performance: The model performs best for "Happy" (85% accuracy on true labels) and struggles with "Fear" (52%) and confuses it with "Sad"(17%) and "Neutral" (9%).

Heat map intensity: Darker blue cells represent higher values, indicating stronger agreement.

Table 4.8 present Model evaluation performance parameters. To calculate precision, recall, and F1-score for each expression calculated with standard formulas. Each value is derived directly from the matrix:

TP: Diagonal value for each class (e.g., 0.58 for Angry).

FP: Sum of the column excluding the diagonal value.

FN: Sum of the row excluding the diagonal value.

$$\text{Precision} = \text{TP} / \text{TP} + \text{FP} \dots\dots\dots (1)$$

$$\text{Recall} = \text{TP} / \text{TP} + \text{FN} \dots\dots\dots (2)$$

F1 - score called harmonic mean of the precision and recall

$$\text{F1-score} = 2 \times \text{Precision} \times \text{Recall} / \text{Precision} + \text{Recall} \dots\dots\dots (3)$$

**Table 4.8: Model performance evaluation parameters
(Expression class wise Precision, Recall, F1-Score)**

Class	Precision	Recall	F1-Score
Angry	0.5321	0.5859	0.5577
Disgust	0.9692	0.6300	0.7636
Fear	0.5149	0.5200	0.5174
Happy	0.7265	0.8586	0.7870
Sad	0.5175	0.5900	0.5514
Surprise	0.8202	0.7300	0.7725
Neutral	0.6019	0.6200	0.6108

4.5 Outcome:

1. Best Precision: Disgust (96.92%), meaning the model rarely predicts Disgust incorrectly.
2. Best Recall: Happy (85.86%), meaning the model captures most happy instances accurately.
3. Best F1-Score: Happy (78.70%), showing a balance between precision and recall.

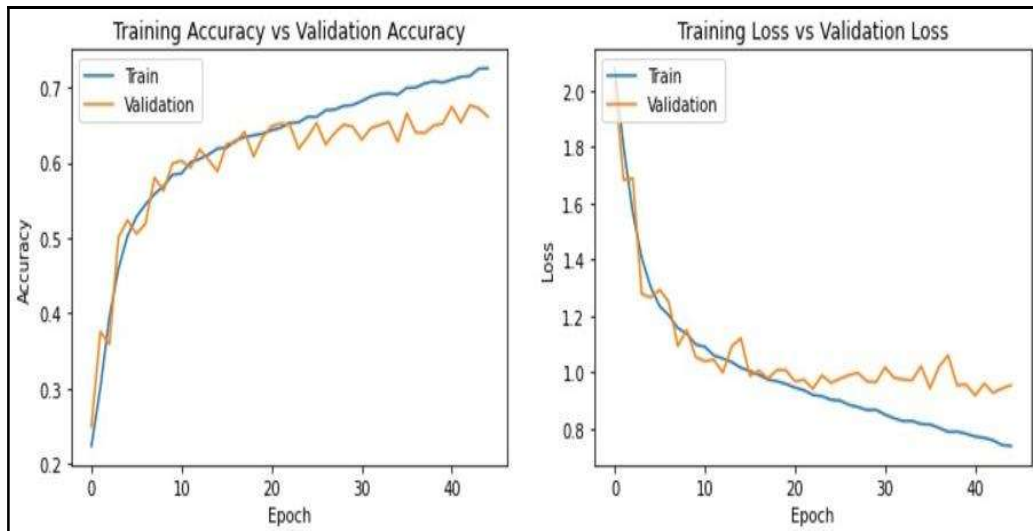


Figure 4.18: Accuracy vs. Epoch & Loss vs Epoch Confusion Matrix

Figure 4.18 shows Accuracy vs. Epoch & Loss vs. Epoch Confusion Matrix. Table 4.9 represent final summary of proposed multi-modal approach for User Responsive

Depression Detection system. We have achieved 68 % of average efficiency of via visual approach of Deep CNN based model and 90% of average efficiency of via S.R.I. with machine learning approach so fusion approach give 79% of overall efficiency of proposed system which use three modalities called Visual features, Self Response Inventory and Colour Psychology respectively.

Table 4.9: Performance of Proposed System

Modality	Accuracy	
(1) Visual feature Base Approach	68%	Deep CNN Base
(2) Self-Response Inventory (S.R.I)	90%	ML based
(3) Colour Psychology Base Approach		
Mutimodal Approach of Proposed System	79 %	Fusion Approach

Table 4.10 represent comparison of proposed method with existing approaches.

Table 4.10: Comparison of proposed method with existing approach performance (where I-Image, A-audio, T-Text, E-EEG, C-Colour, S-S.R.I. respectively)

Ref No.	Year	Modality						fusion	Dataset	Accuracy
		I	A	T	E	C	S			
[19]	2015	√	√					Decision level	Fer+tfd	47.67
[22]	2017	√	√					Decision level	Recola	76.00
[23]	2018	√	√	√				Decision level	Cmu-mosei	49.10
[25]	2018	√	√	√				Feature level	Iemocap	77.60
[28]	2020		√	√				Feature level	Iemocap	80.51
[29]	2022	√	√		√			FL, DL, HL	Ravdess, EEG	78.75
[30]	2022	√	√	√	√			Weighted decision level	Combined Customized	93.00
[30]	2022	√	√	√	√			Weighted decision level	Real-world collected dataset	67.00
[41]	2024	√	√	√				Feature level	DAIC-WOZ dataset	81.01
Proposed Approach	2025	√				√	√	Weighted decision level	FER-2013 Tested with wild data	79.00

4.6 Achievements with respect to Objectives:

Objective 1: Drive deeper into existing depression detection system.

Achievement: Paper – Publication (1) “Depression Detection System: A Systematic Review” is the outcome of this objective in which domain related research are examined.

Objective 2: Developed a user-friendly real-time, multimodal depression detection system.

Achievement: Paper – Publication (2) “User Responsive Automatic Method for Real Time Depression Detection Using Deep Neural Network” is the outcome of this objective

The proposed depression detection system is user friendly, real-time, multimodal, user-responsive, reliable and confidential really a boon in health care domain in near future for pre-screening of depression symptoms compared to existing practices and its complex operating mechanism. Tool effectively identified depression with response from Self Response Inventory (S.R.I.) quiz, Visual features and colour selection with almost 79% accuracy.

Objective 3: To validate the proposed method through performance parameters.

Achievement: Validation including confusion matrix, class-wise precision/recall/F1 values confirmed the robustness of model. Paper publication (2) is the outcome of objective 2 & 3.

Objective 4: Apply the tool in wild conditions to confirm its operability, reliability and effectiveness.

Achievement: The tool is performing effectively on real time camera taken picture frame and video sequences, demonstrating strong generalization and reliability in real-world scenarios.

Objective 5: Validate Automatic mood detection tool: Self Response Inventory

Achievement: Paper publication (3) is the outcome of this objective which effectively validate on 150 participants.

CHAPTER– 5

Conclusion, Major Contribution, and Future Scope

5.1 Conclusion:

This chapter highlights the research work presented in this thesis. It focuses primary contributions and summarizes the results of our research work. It also discusses the various possibilities for future research in this domain:

- Depression is among leading cause of disability in each age group globally which affects health care system severely. Millions of affected persons require psychological and/or clinical treatments. It more affected to woman as before and after pregnancy changes in body. Teenagers are more emotional vulnerable and more connection to internet, social media, virtual world make situations worst. If negative state of mind / mental health issues / depression can be detected in initial stage it can be cured with little care else situation may become worst.



Figure 5.1: Understanding and Overcoming Mental Health Challenges [57]

- Depression detection tool is highly demanded in current scenario and multi modal approach give more surety of results with various modalities are fused in screening test so we can easily conclude the emotions or mood of the person and alert or cure them immediately.
- As prevention is better and easy to cure and thus, we can also reduce the clinical burden, cost and also overcome with social stigma of mental health and can make together **“World better and stronger Physically and Mentally”**
- Depression is among leading cause of disability in each age group globally which affects health care system severely. Millions of affected persons require psychological and/or clinical treatments. It more affected to woman as before and after pregnancy changes in body. Teenagers are more emotional vulnerable and more connection to internet, social media, virtual world make situations worst. If negative state of mind / mental health issues / depression can be detected in initial stage it can cure with little care else situation may become worst.
- This research is dedicated to such pre-diagnostic self-automated tool which can produced reliable result by performing fusion of available classical methods. This research is a novel approach which analyzes classical Self Response Inventory (S.R.I) and Visual features of person without intervention of other person so one can be more confidential and reliable result can be produced if tool is operated in an honest and truthful manner multi modal approaches give significant result so such automated tool really a boon in mental health care domain in near future for pre-screening of depression symptoms.
- Multimodal depression detection tool take input from

(1) Camera for live image and video

(2) Stored file in forms of picture and video

and decide the emotions of a person which can be classified as positive emotion (Happy) with 85% and Negative emotions (Sad, Angry, Disgust,

Contempt) and Neutral and Surprise are considered as neither Positive nor Negative. If person is detected in Positive or Neutral mood then no need to worry but if person have continuously negative emotions as outcome he / she is advised to take care of mental health seriously.

(3) Self Response Inventory (S.R.I.) which is specific questionnaires approach derived from 10 such instruments of Depression Detection and give efficiency near 90%.

- In our proposed S.R.I. method one question related to colour psychology is also included for colour selection so based on selected colour Person's psychology emotional status of a person can be decided so via all three modalities called Visual, S.R.I. and colour psychology we can conclude the emotions or mood of the person in simple, real-time, user responsive manner.

5.2 Major Contribution:

This thesis explores diverse methodology related to depression detection and come out with the proposed depression detection system which is user friendly, real-time, multimodal, user-responsive, reliable and confidential really a boon in health care domain in near future for pre-screening of depression symptoms compared to existing practices and its complex operating mechanism.

- Proposed system fuses visual features of face, S.R.I. and colour psychology approach.
- To validate the proposed model, real-world data was collected from various person and outcome is also included in pictorial form of chapter-4 which give 68% accuracy with Visual feature-based approach.
- S.R.I approach is also validated with 150 person based on past 2-3 days experience compared to 2-week long feedback of person and it also give accuracy of 90%, Overall, this proposed approach gives 79% accuracy on real world data samples.
- Thesis contributes by developing multimodal depression detection tool based on Users response it validates in satisfactorily in real-life conditions.

5.3 Future Scope:

Proposed system gives 79% accuracy still model's performance could be improved for emotions like Fear, Sad, and Neutral where mis-classifications are significant higher. Further by following actions Proposed system performance can be further improved

- The participants' number could be increased performance of model.
- Quality of camera plays a major role so high-quality images contain visual features can retrieve more specific information which strengthen the dynamics of visual behavioral analysis.
- Add on more modalities like verbal features, social media text, or Bio instrumentation approach could be improve the outcome of Proposed system.
- Overall, the proposed system / tool effectively meets the established research objectives, creating a confidential, user responsive reliable result in Use friendly manner which comply our Research Goal and Objectives.

List of References

- [1] 2021 Global Burden of Disease (GBD) [online database]. Seattle: Institute for Health Metrics and Evaluation; 2024 (<https://vizhub.healthdata.org/gbd-results/>, accessed 13 August 2025).
- [2] Woody CA, Ferrari AJ, Siskind DJ, Whiteford HA, Harris MG. A systematic review and meta-regression of the prevalence and incidence of perinatal depression. *J Affect Disord.* 2017;219:86–92.
- [3] Evans-Lacko S, Aguilar-Gaxiola S, Al-Hamzawi A, et al. Socio-economic variations in the mental health treatment gap for people with anxiety, mood, and substance use disorders: results from the WHO World Mental Health (WMH) surveys. *Psychol Med.* 2018;48(9):1560-1571.
- [4] P. Ekman, *Handbook of Cognition and Emotion*, John Wiley & Sons Ltd, 2005, pp. 45-60
- [5] H. Ellgring, R. J. Eiser, K. R. Scherer, "Non-verbal Communication in Depression," Cambridge University Press, 2007.
- [6] American Psychiatric Association (5th edition, 2013). *Diagnostic and statistical manual of mental disorders*. Washington: DC.
- [7] Katikalapudi, Raghavendra, Sr noiram Chellappan, Frances Montgomery, Donald Wunsch, and Karl Lutzen. "Associating internet usage with depressive behavior among college students." *IEEE Technology and Society Magazine* 31, no. 4: 73-80. 2012.
- [8] Alghowinem S, Goecke R, Wagner M, Parker G, Breakspear M (2013). Eye movement analysis for depression detection. In *IEEE International Conference on Image Processing*, 4220–4224.
- [9] Alghowinem S, Goecke R, Wagner M, Parker G, Breakspear M: Head pose and movement analysis as an indicator of depression. In *Humaine Association Conference on Affective Computing and Intelligent Interaction* 2013:283–288.
- [10] Jeffrey M Girard, Jeffrey F Cohn, Mohammad H Mahoor, S Mohammad Mavadati, Zakia Hammal, and Dean P Rosenwald, "Nonverbal social withdrawal in depression: Evidence from manual and automatic analyses," *Image and vision computing*, pp. 641-647, 2014
- [11] Ooi KEB, Lech M, Allen NB (2013). Multi-channel weighted speech classification system for prediction of major depression in adolescents. *IEEE Transactions on Biomedical Engineering*, 60:497–506.
- [12] Cummins N, Sethu V, Epps J, Krajewski J (2014). Probabilistic acoustic volume analysis for speech affected by depression. In *Annual Conference of the International Speech Communication Association*, 1238–1242.

- [13] Williamson JR, Street W, Quatieri TF, Helfer BS, Ciccarelli G, Mehta DD: Vocal and Facial Biomarkers of Depression Based on Motor Incoordination and Timing. In Proceedings of the 4th International Workshop on Audio/Visual Emotion Challenge 2014:65–72.
- [14] Espinosa HP, Escalante HJ, Villasen~orpineda L, Montes-y g´omez M, Pinto-Avedan~oD, Reyes-Meza V: Fusing affective dimensions and audio-visual features from segmented video for depression recognition. In ACM International Workshop on Audio/Visual Emotion Challenge 2014.
- [15] Gupta R, Malandrakis N, Xiao B, Guha T, Van Segbroeck M, Black MP, Potamianos A, Narayanan SS: Multimodal prediction of affective dimensions and depression in human - computer interactions. In International Audio/Visual Emotion Challenge and Workshop 2014
- [16] Senoussaoui M, Sarria-Paja M, Santos JaF, Falk TH: Model Fusion for Multimodal Depression Classification and Level Detection. In Proceedings of the 4th International Workshop on Audio/Visual Emotion Challenge 2014:57–63.
- [17] Pampouchidou, Anastasia, Kostas Marias, Manolis Tsiknakis, P. Simos, Fan Yang, and Fabrice Meriaudeau (2015). Designing a framework for assisting depression severity assessment from facial image analysis. In Signal and Image Processing Applications (ICSIPA), International Conference on, pp. 578-583, IEEE.
- [18] Z. Hammal, J. F. Cohn, C. Heike, and M. L. Speltz. What Can Head and Facial Movements Convey about Positive and Negative Affect? In Affective Computing and Intelligent int.2015.
- [19] S. E. Kahou, X. Bouthillier, P. Lamblin, C. Gulcehre, V. Michalski, K. Konda, S. Jean, P. Froumenty, Y. Dauphin, N. Boulanger-Lewandowski, R. Chandias Ferrari, M. Mirza, D. Warde-Farley, A. Courville, P. Vincent, R. Memisevic, C. Pal, and Y. Bengio, “Emonets: Multimodal deep learning approaches for emotion recognition in video,” *Journal on Multimodal User Interfaces*, vol. 10, no. 2, pp. 99–111, 2015.
- [20] Sahla, K. S., and T. Senthil Kumar. "Class room Teaching Assessment Based on Student Emotions. "In the International Symposium on Intelligent Systems Technologies and Applications, pp. 475-486. Springer International Publishing, 2016.
- [21] Morales, M., Scherer, S., & Levitan, R, "A Cross-modal Review of Indicators for Depression Detection Systems," Proceedings of the Fourth Workshop on Computational Linguistics and Clinical Psychology -- From Linguistic Signal to Clinical Reality, 2017
- [22] P. Tzirakis, G. Trigeorgis, M. A. Nicolaou, B. W. Schuller, and S. Zafeiriou, “End to-End Multimodal Emotion Recognition Using Deep Neural Networks,” *IEEE Journal of Selected Topics in Signal Processing*, vol. 11, no. 8, pp. 1301–1309, Dec. 2017, doi:10.1109/jstsp.2017.
- [23] S. Sahay, S. H. Kumar, R. Xia, J. Huang, and L. Nachman, “Multimodal relational

tensor network for sentiment and emotion classification,” Proceedings of Grand Challenge and Workshop on Human Multimodal Language (Challenge-HML), 2018.

[24] Dr. D. Venkataraman and Namboodiri Sandhya Parameswaran: “Extraction of Facial Features for Depression Detection among Students” International Journal of Pure and Applied Mathematics Volume 118 No. 7 2018, 455-463.

[25] D. Hazarika, S. Poria, A. Zadeh, E. Cambria, L.-P. Morency, and R. Zimmermann, “Conversational memory network for emotion recognition in dyadic dialogue videos,” Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers), 2018.

[26] A. Pampouchidou, P.G. Simos, K. Marias, F. Meriaudeau, F. Yang, M. Pediaditis, M. Tsiknakis, "Automatic Assessment of Depression Based on Visual Cues: A Systematic Review," IEEE Transactions on Affective Computing, vol. 10, no. 4, pp. 445-470, 2019.

[27] M. M. Hassan, Md. G. R. Alam, Md. Z. Uddin, S. Huda, A. Almogren, and G. Fortino, “Human emotion recognition using deep belief network architecture,” Information Fusion, vol.10.1016/j.inffus.2018.10.009. 51, pp. 10–18, Nov. 2019

[28] D. Priyasad, T. Fernando, S. Denman, S. Srnoidharan, and C. Fookes, “Attention driven fusion for multi-modal emotion recognition,” ICASSP 2020 - 2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2020.

[29] J. Njoku, Angela C. Caliwag, W. Lim, S. Kim, H.-J. Hwang, and J.-W. Jeong, “Deep Learning Based Data Fusion Methods for Multimodal Emotion Recognition,” The Journal of Korean Institute of Communications and Information Sciences, vol. 47, no. 1, pp. 79–87, Jan. 2022, doi: 10.7840/kics.2022.47.1.79.

[30] Komal D. Anadkat, Dr. Hiteishi M. Diwanji & Dr. Shahid Modasiya “Effect of Preprocessing in Human Emotion Analysis Using Social Media Status Dataset” Reliability: Theory and Application “ISSN 1932-2321, Volume 17 Issue 1 PP-67 March 2022 (SCOPUS).

[31] Jonauskaite, D., Abu-Akel, A., Dael, N., Oberfeld, D., Abdel-Khalek, A. M., Al-Rasheed, A. S., Antonietti, J.-P., Bogushevskaya, V., Chamseddine, A., Chkonis, E., Corona, V., Fonseca-Pedrero, E., Griber, Y. A., Grimshaw, G., Hasan, A. A., Havelka, J., Hirnstein, M., Karlsson, B. S. A., Laurent, E., Mohr, C. (2020). Universal Patterns in Colour-Emotion Associations Are Further Shaped by Linguistic and Geographic Proximity. *Psychological Science*, 31(10), 1245-1260.

[32] Yang J, Shen X. The Application of Colour Psychology in Community Health Environment Design. *J Environ Public Health*. 2022 Aug 25; 2022:7259595. doi: 10.1155/2022/7259595. Retraction in: *J Environ Public Health*. 2023 Oct 18; 2023: 9786523. doi: 10.1155/2023/9786523. PMID: 36060888; PMCID: PMC9436572

[33] Hamilton M. A rating scale for depression (1960). *Journal of neurology, neurosurgery, and psychiatry*, 23 (1):56.

- [34] Beck AT, Steer RA, Ball R, Ranieri WF. (1996). Comparison of beck depression inventories-i a and -iii n psychiatric out patients. *Journal of personality assessment*, 67(3):588–597.
- [35] Patient Health Questionnaire-9, Kroenke, K., Spitzer, R. L., & Williams, J. B. W. (1999). Patient Health Questionnaire-9 (PHQ-9) [Database record]. APA SysTest.
- [36] Levis B, Benedetti A, Thombs B D. Accuracy of Patient Health Questionnaire-9 (PHQ-9) for screening to detect major depression: individual participant data meta-analysis *BMJ* 2019; 365: 11476 doi:10.1136 / bmj. 11476
- [37] Zung, WW (1965) A self-rating depression scale. *Arch Gen Psychiatry*12,63-70.
- [38] Radloff, L.S. (1977). The CES-D Scale: a self-report depression scale for research in the general population. *Applied Psychological Measurement*,1: 385-401.
- [39] Whooley, M.A., Avins, A.L., Miranda, J. et al. Case-finding instruments for depression. *J GEN INTERN MED* 12, 439–445 (1997). <https://doi.org/10.1046/j.1525-1497.1997.00076.x>
- [40] Rush A, Trivedi M, Ibrahim H et al. The 16-Item quick inventory of depressive symptomatology (QIDS), clinician rating (QIDS-C), and self-report (QIDS-SR NO): a psychometric evaluation in patients with chronic major depression, *Biological Psychiatry*, 54, 573-583
- [41] Yang, S., Cui, L., Wang, L., Wang, T., & You, J. (2024). Enhancing multimodal depression diagnosis through representation learning and knowledge transfer. *Heliyon*, 10(4), e25959. <https://doi.org/10.1016/j.heliyon.2024.e25959>
- [42] Internet resources like: doc player.net, journal of bigdata., springeropen.com, deepai.org, arxiv.org, pubmed.ncbi.nlm.nih.gov etc.
- [43] <https://www.nimh.nih.gov/health/statistics/major-depression> etc.
- [43] <https://www.verywellmind.com/colour-psychology-2795824>.
- [44] R. Verma, “FER2013,” Kaggle, 26-May-2018.
- [45] Argyle, Michael (1976). Non-verbal Communication and Language. *Royal Institute of Philosophy Lectures* 10:63-78.
- [46] M. Egger, M. Ley, and S. Hanke, “Emotion recognition from Physiological Signal Analysis: A Review,” *Electronic Notes in Theoretical Computer Science*, vol. 343, pp. 35–55, 2019.
- [47] C. Zucco, B. Calabrese and M. Cannataro, “Emotion Mining: From Unimodal to Multimodal Approaches,” https://link.springer.com/chapter/10.1007/978-3-030-82427-3_112021.
- [48] P. Ekman and W. V. Friesen, *Unmasking the face: A guide to recognizing emotions*

from facial clues. Cambridge, MA: Malor Books, 2003.

[49] A. Talipu, A. Generosi, M. Mengoni, and L. Giraldi, "Evaluation of deep convolutional neural network architectures for emotion recognition in the wild," 2019 IEEE 23rd International Symposium on Consumer Technologies (ISCT), 2019.

[50] B. Taha and D. Hatzinakos, "Emotion recognition from 2D facial expressions," 2019 IEEE Canadian Conference of Electrical and Computer Engineering (CCECE), 2019.

[51] D. K. Jain, P. Shamsolmoali, and P. Sehdev, "Extended deep neural network for facial emotion recognition," Pattern Recognition Letters, vol. 120, pp. 69–74, Apr. 2019, doi: 10.1016/j.patrec.2019.01.008.

[52] Available: <https://www.weforum.org/stories/2024/05/mental-stress-bodies-health-awareness/> / How stress moves from the mind to Body parts (Mental Health Challenges image: rawpixel.com)

[53] Available: [blogs.NVIDIA.com: What is AI Computing?](https://blogs.nvidia.com/what-is-ai-computing/) [Online].

[54] Available: [Medium.com CNN: Guide for your first project](https://medium.com/cnn/guide-for-your-first-project), [online].

[55] Available: [Research Gate.com: Illustration of Face Segment](https://www.researchgate.net/publication/328111111), [online].

[56] Available: [Emotiva: Displays of Various Action Units \(AUs\)](https://www.emotiva.com/displays-of-various-action-units-aus), [Online].

[57] Available: <https://khanlaila.com/overcoming-mental-health-challenges-in-adults/>, [online].

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Availablefrom: <https://www.jneonatalurg.com/index.php/jns/article/view/8117/9194>

(3) Acharya JP, Shah D. Automatic mood detection tool: Self Response Inventory. International Research Journal of Engineering and Technology.2026 Feb;13(02): 821- 826

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User Responsive Automatic Method for Real-Time Depression Detection Using Deep Neural Network

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ABSTRACT

During last one decade the mental health is becoming a major concerning issue to society as number of various socio - economical, personnel and societal issues related to mental health are increased in exponential manner. Depression is mood disorders which result in severe disabling conditions which affect person's ability to cope with routine life and real-life challenges which are dynamic in nature. It may occur when person remain more than two weeks in negative state of mind continuously. Depression has observable behavioral symptoms related to affective and psychomotor domains which can be identified. Classical approaches majorly depend on person's behavioral analysis and family observations during clinical interviews, which are effective if it can be precisely defined and assessed but persons have tendency to conceal it so they are less effective while proposed method with Deep Learning techniques perform the said task with accuracy of 79% and open a new era for health care domain.

Keywords: Mental health, Depression, SRI, PHQ-9, DMI-10, Visual behavioral analysis, Audio Video Emotion Challenge (AVEC), Visual features, DSM, Deep Neural Network (DNN) etc.

1. INTRODUCTION

Depression will be leading cause of disability globally in all age groups which severely affects the global health index and social impact. It is an ongoing problem which may resolve with proper care but may reoccur via various risk factors. The medical community does not fully understand the causes of depression but mostly known various risk factors like environmental, psychological, social, financial factors, drug addictions change in genetic features, brain's neurotransmitter levels, and accidental events. Early detection plays a crucial role as by positive counseling, various physical and mental exercises like meditation and proper medication may resolve depression else situations become worst up to suicidal tendency. Human are expressive through verbal and nonverbal communication channels both channels are important to express feelings [1], [2]. Person can remain silent to suppress verbal communication and by fake expression or conceal expression can hide real scenario still researcher believes that facial expression is crucial input to present emotional status of person so psychologists try to map facial expressions to emotional states. When Person is feeling depression both verbal and nonverbal channel give strong indicators [3]. Number of researchers has contributed their work to identify depression which closely related with psychology, affective, computer and clinical domains so in real time it's a multi-challenging task. As domain start with Psychology, Computer Science and Clinical domain and last long to social domain the major key challenges are mentioned as under to map psychological domain to computer and validate it with behavioral/clinical predictions [4], [5].

2. METHODS

Human express their emotions through multiple channels which can be monitored for emotion analysis.[3],[4],[5]. There are many approaches like Clinical, Visual, Verbal, Colour psychology, Self Response clinical inventory, EEG [6]etc. to determine the mental health of a person Major contribution of specific domain is as under.

Table 1: Authors contribution of domain related research

S r	Authors	Type	Dataset
1	Becker et al. (1994)	Audio/Video	Dementia Bank Database Reddit Self-reported
2	Valstaret al. (2013)	Audio/Video	AVEC 2013
3	Pradhan et al. (2014)	Text data	SemEval-2014 Task 7
4	Lieberman et al. (2013)	Text data	Crisis Text Line
5	Valstaretal. (2014)	Audio/Video	AVEC 2014
6	Gratch J et al. (2014)	Audio/Video	The Distress Analysis Interview Corpus
7	Valstaretal. (2016)	Audio/Video	AVEC 2016
8	Videbech (2016)	Audio/Video /Report	The Danish Depression Database
9	Yates et al. (2017)	Text data	Depression Diagnosis (RSDD) dataset
10	Garcia-Ceja et al. (2018)	Audio/Video	Depression
11	Komal Anadkat et al. (2022)	Audio/Video/Social media text/EEG	FER2013, Ravdess, Kaggle's social media dataset, and EEG dataset

Visual as major channel for detection:

Face is the major channel of emotions indication. People reflect their feelings knowingly or unknowingly by their facial expression so face is considered as prime part of body for expression so based on this fact Ekman [1] categorize standard expression of six fundamental feelings along with Head orientation, posture and movement majorly use to recognize depression [7], [8]. Girard et al [9] explore strong co-relation between visual direction and depression.

Table 2: List of major Visual Features for Behaviour Detection

Features	Association with Facial Features
1	Eyelid opening /squinting movement
2	Outward appearance event with inconstancy with force
3	Head appearance with direction and deployment
4	Face movement
5	Pupil enlargement/inclination
6	Iris development
7	Grin force and term
8	Eye stare
9	Dismissal articulation/negative event
10	Mouth corner appearance

In Colour psychology-based approach reveals how various colours impact person's mood and so behaviors. It enlightens colour impact on person's emotional response based on age and cultural background etc. [10]. Major evidence in this emerging area is based on the feedback result of anecdotal, but domain expert has made a few important conclusions that how colour theory correlate with behaviors. In 2020 study that surveyed the emotional associations of 4598 persons from 30 countries and conclude that people commonly associate certain colours with specific emotions as below:

Table 3: Colour association with Emotion and Mood

Colour	Percentage	Emotions	Mood Category
Black	51%	Sad	negative
White	43%	Relief	Positive
Red	68%	Love	Positive
Blue	35%	Relief	Positive
Green	39%	Contentment	negative
Yellow	52%	Joy	Positive
Purple	25%	Pleasant	Positive
Brown	36%	disgust	negative
Orange	44%	Joy	Positive
Pink	50%	Love	Positive

Many contributors used fusion of above in specific group called multi-modal data in which persons reflect their feelings through multiple channels [11], [12]. Which are more accurate and reliable than focusing only on a single modal like audio, video, text, or EEG etc. [6].

Real-time depression detection methodology:

This research develops a depression detection system which incorporates multiple data as inputs from image, video (stored and live) [] and response provided by user in quiz assessment. as shown in Fig. 1. Data acquisition, data processing, system construction, and model performance evaluation are described as follows

Model take input data from various channels like camera for static and video images input, Stored image and/or video upload options for testing is also available and third input is of quiz in which user response are process and based on the outcomes of all channels person's negative mood and its severity is identify.

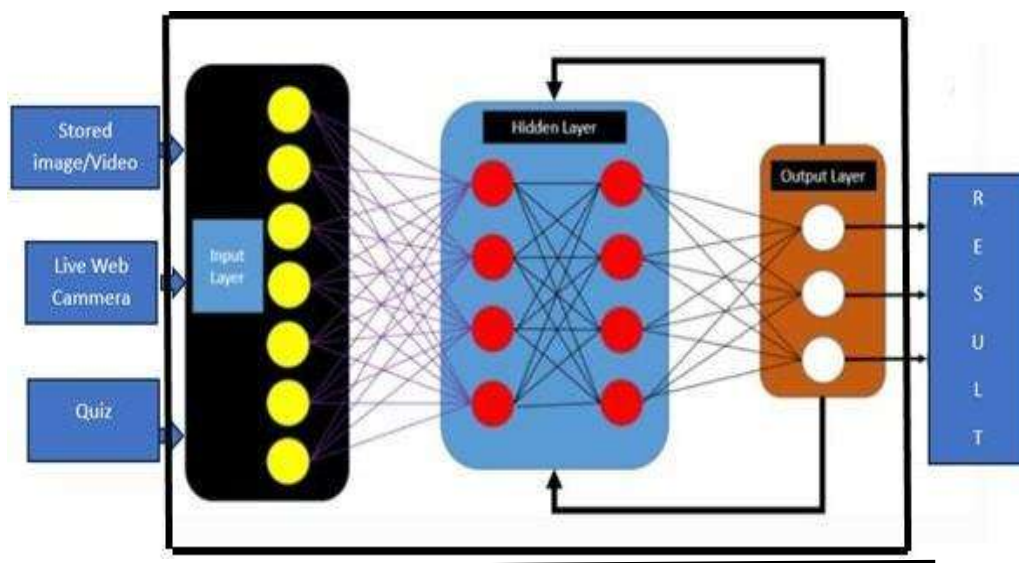


Figure 1: Depression detection Deep neural network model



Figure 2: Prototypic Facial Expression



Figure 3: Testing Facial Expression intra-class variability



Figure 4: Testing Facial Expression inter-class variability

As shown in above figure face images are classified broadly into positive and negative groups. Happy is positive bias images where Sad, Fear, Angry, Surprise and Disgust are negative biased images. Neutral has no biasing as per its name.

Data acquisition:

Depression detection model obtained data from three sources which are static/dynamic images capture from camera both live and stored and quiz responses.

Data channel 1: Input image from Camera in real time video

Image and/or Video from camera is captured and continuously images are identified in categorical expression and positive and negative expression is determined. As shown in above figure face images are classified broadly into positive and negative

groups. Happy is positive bias images where Sad, Fear, Angry, Surprise and Disgust are negative biased images. Neutral has no biasing as per its name.

Data channel 2: Stored image and video

Stored Image and/or Video from camera is captured and continuously images are identified in categorical expression and positive and negative expression is determined.

Data channel 3: Quiz response

First Quiz has unique general questionnaires associate with physical and mental health based on the answer selected by user it categorizes person's mood at Neutral, Happy and Sad identified from quiz response based on past 2 or 3 days experience.

Table 4: Self Response Inventory

Sr	Question (Select option based on past 2-3 days experience)	Outcome	Yes	No	Not Decided
1	Have you taken enough sleep?	Rest			
	Evaluates your physical well-being and rest. Adequate sleep is essential for health and productivity.				
2	Have you taken enough healthy food (in bf / lunch /dinner)?	Food			
	Assesses whether you're meeting your nutritional needs for energy and overall health.				
3	Have you done any exercise/yoga/workout?	Exercise			
	Reflects your physical activity levels, which are important for maintaining health, fitness, and mental well-being.				
4	Are you enjoying your daily routine?	Enjoyment			
	Indicates satisfaction and contentment with your daily life and habits.				
5	Can you select your clothes by yourself?	Decision			
	Measures independence and autonomy in decision-making and self-care.				
6	Can you prepare / suggest foods? (For bf / lunch /dinner)?	Selection/Creativity			
	Evaluates self-sufficiency in meal planning and preparation.				
7	Have you interact with your family members to share your thoughts or feelings?	Sharing feelings			
	Assesses emotional connectivity and communication with loved ones.				
8	Are you comfortable to communicate with your neighbours/colleagues/or friends?	Communication			
	Measures your social comfort and ability to engage with people in various settings.				
9	Do you spare some time to do your liking things?	Hobby /liking			
	Reflects your balance between responsibilities and personal enjoyment or hobbies.				
10	Can you read newspaper/books/articles easily?	Concentration			
	Evaluates cognitive function, literacy, and engagement with information.				
11	Can you watch TV/mobile/Movie easily?	Concentration			
	Measures ease of leisure activity and mental relaxation.				
12	Are you satisfied with your individual achievement/contribution to family/Society?	Self role			

	Reflects self-assessment of your accomplishments and your sense of purpose and fulfillment of your efforts and knowledge/Skills and attitude.			
13	Do you have interest in things which appeal you a lot previously?	Active Participation		
	Examines personal interests and desires related to romantic/pleasure connections.			
14	Do you feel your life going smoothly?	Satisfaction		
	Reflects your perception of life's trajectory and personal well-being.			
15	Do you feel tomorrow is better than present?	Optimistic		
	Indicates optimism and hope for the better future.			
16	Do you feel you are unique and no one can replace yourself?	Self-esteem		
	Reflects self-worth and a sense of individuality.			
17	Do you feel stress of your study/work /responsibilities?	Stress		
	Whether you experience feelings of pressure, anxiety, or overwhelm due to your academic, professional, or personal duties.			
18	Do you feel nothing going on track and after a lots of efforts from your side u can't do anything?	Out of control situation		
	if you ever feel like, despite putting in a lot of hard work and effort, things still aren't progressing as they should. It reflects a sense of frustration or helplessness,			
19	Do you feel frustrated or aloneness?	Helplessness		
	Reflects feelings of frustration, helplessness, or burnout. The outcome of this question could reveal several underlying emotional or psychological states, such as: Frustration or Disappointment, Helplessness or Powerlessness, Burnout, Lack of Progress or Direction, Self-Doubt.			
20	Selection of Colour base on your mood from these: Black/Yellow/Red/None	Colour		
	Mood association with colour.			
21	Have you come across with negative thoughts /suicidal thoughts?	Negative		
	Negativity			

If person having negative response to more than 7 questions of above it suggest negative mood of the person .Depending on the outcome of mood response from all of three channels are negative traditional Depression detection test PHQ-9[14] is suggested and based on the scores obtained from responses given in the quiz score is converted from numeric to depression outcome. The scores are converted in three classes as follows:

Table 5: Classification of S.R.I. Score

Sr	Score range	Level	Depression	Actions
1	0-4	Level 0	No Depression	Stay healthy physically and mentally
2	5-8 points	Level 1	Slight Depression	Repeat test, Take care of your mental health
3	9-14 points	Level 2	Moderate Depression	Repeat test ,still result is same advisable to consult medical professional
4	more than 15 points	Level 3	High Depression	Immediately consult medical professional

Model Architecture:

Deep Learning model of CNN (Convolution Neural Network) is used for creating, training and analyze expression from static image and video channels. Major components of the architecture are as below:

1. Convolution Layers: Multiple Convolution layers to extract features from images using multiple filters (32,64,128,256) of kernel sizes (3 x 3) which extract features from images.
2. Rectified Linear Unit (ReLU): function used for the introduction.
3. MaxPooling layers: perform reduction of spatial dimension reduction so computational complexity also reduced.
4. Dropout: this layer drops randomly some nodes in training phase so model does not have tendency of Over fitting.
5. Flatten Layer : Converts the 2D feature maps into a 1D vector for input to dense layers.
6. Dense Layers: These are fully connected layers for seven expression classifications

Above layers include Image Pre-processing, Data Augmentation, data generation, training and Validation.

3. RESULTS**Table 6: Model performance evaluation**

Epoch	Training Loss	Training Accuracy	Validation Loss	Validation Accuracy
1	2.2673	0.2043	2.0278	0.2493
2	1.8677	0.2697	1.6808	0.3757
3	1.6180	0.3736	1.6879	0.3589
4	1.4435	0.4470	1.2770	0.5007
5	1.3103	0.4982	1.2653	0.5237
6	1.2351	0.5255	1.2923	0.5056
7	1.2070	0.5357	1.2488	0.5189
8	1.1475	0.5628	1.0932	0.5803
9	1.1403	0.5671	1.1497	0.5628
10	1.0962	0.5850	1.0529	0.5992
11	1.0821	0.5887	1.0385	0.6027
12	1.0651	0.5986	1.0442	0.5936
13	1.0482	0.6021	0.9976	0.6180
14	1.0344	0.6097	1.0922	0.6041
15	1.0152	0.6157	1.1200	0.5887
16	0.9960	0.6218	0.9868	0.6250
17	0.9973	0.6255	1.0060	0.6271
18	0.9561	0.6398	0.9771	0.6411
19	0.9605	0.6380	1.0074	0.6082
20	0.9468	0.6449	1.0069	0.6341
21	0.9391	0.6445	0.9674	0.6487
22	0.9247	0.6490	0.9729	0.6522

23	0.8960	0.6622	0.9405	0.6508
24	0.9082	0.6603	0.9881	0.6187
25	0.8918	0.6643	0.9616	0.6341
26	0.8988	0.6594	0.9764	0.6529
27	0.8824	0.6713	0.9893	0.6243
28	0.8660	0.6786	0.9972	0.6397
29	0.8636	0.6774	0.9671	0.6508
30	0.8598	0.6847	0.9640	0.6459
31	0.8403	0.6897	1.0170	0.6501
32	0.8273	0.6951	0.9798	0.6543
33	0.8183	0.6951	0.9737	0.6278
34	0.8195	0.6944	0.9706	0.6655
35	0.8011	0.6966	1.0212	0.6404
36	0.8174	0.6997	0.9421	0.6397
37	0.7934	0.7029	1.0191	0.6404
38	0.7851	0.7029	1.0593	0.6397
39	0.7841	0.7100	0.9531	0.6494
40	0.7779	0.7063	0.9565	0.6522
41	0.7669	0.7110	0.9169	0.6745
42	0.7594	0.7183	0.9593	0.6536
43	0.7406	0.7243	0.9267	0.6767
44	0.7310	0.7318	0.9420	0.6725
45	0.7191	0.7329	0.9537	0.6613

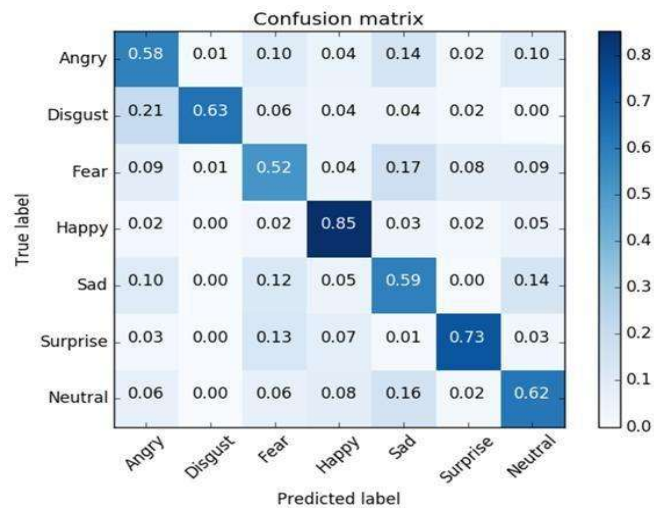


Figure 5: Confusion Matrix

Database:

The FER2013 is an open dataset (Facial Expression Recognition 2013) [13] which consists of facial images along with their emotion categories of a person. The database has facial images of size 48×48 pixels of monochrome images with seven different categories of emotions: Angry, Disgust, Fear, Happy, Sad, Surprise, and Neutral. The dataset has 28,709 images in the training set and 3,589 images in the testing set.

Confusion matrix of model represents:

True label (rows): The actual emotions present in the dataset (e.g., Angry, Disgust, etc.).

Predicted label (columns): The emotions predicted by the classification model.

Each cell contains the proportion of samples predicted for a given emotion compared to the true label.

Key observations:

1. Diagonal values 0.58 for angry, 0.85 for Happy represent correct predictions. Higher values along the diagonal indicate better performance for that specific emotion. The model predicts "Happy" correctly with 85% and "Neutral" correctly 62% of the time so remaining emotions are negative or converge to negative emotions.
2. Off-diagonal values: represent misclassifications where the model incorrectly predicts a different emotion. e.g. "Angry" is misclassified as "Fear" 10% of the time; "Neutral" is sometimes predicted as "Sad" (16%) etc.
3. Best and worst performance: The model performs best for "Happy" (85% accuracy on true labels) and struggles with "Fear" (52%) and confuses it with "Sad" (17%) and "Neutral" (9%).
4. Heat map intensity: Darker blue cells represent higher values, indicating stronger agreement.

To calculate precision, recall, and F1-score for each expression calculated with standard formulas. Each value is derived directly from the matrix:

1. TP: Diagonal value for each class (e.g., 0.58 for Angry).
2. FP: Sum of the column excluding the diagonal value.
3. FN: Sum of the row excluding the diagonal value.

Table 7: Model performance evaluation

Class	Precision	Recall	F1-Score
Angry	0.5321	0.5859	0.5577
Disgust	0.9692	0.6300	0.7636
Fear	0.5149	0.5200	0.5174
Happy	0.7265	0.8586	0.7870
Sad	0.5175	0.5900	0.5514
Surprise	0.8202	0.7300	0.7725
Neutral	0.6019	0.6200	0.6108

Observations:

1. Best Precision: Disgust (96.92%), meaning the model rarely predicts Disgust incorrectly.
2. Best Recall: Happy (85.86%), meaning the model captures most Happy instances accurately.
3. Best F1-Score: Happy (78.70%), showing a balance between precision and recall.

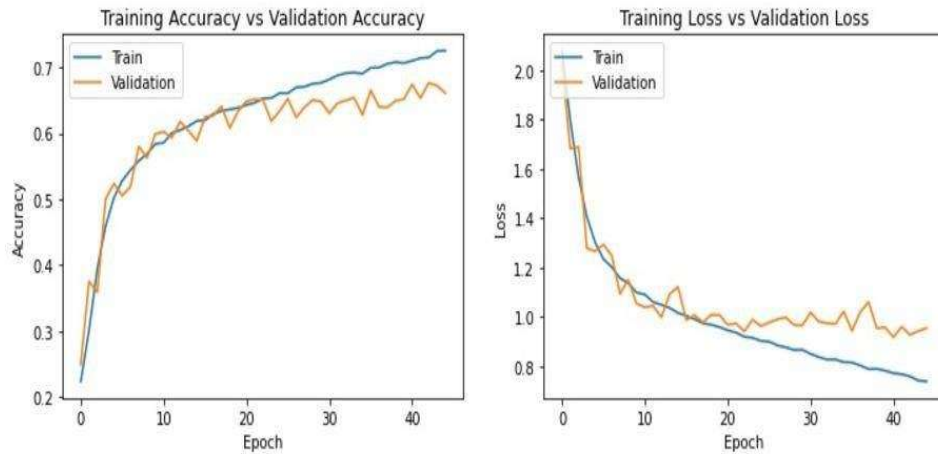


Figure 6: Accuracy vs Epoch & Loss vs Epoch on the Confusion Matrix

• **Table 8: Comparison of Proposed Method with Existing Approaches**

Ref No.	Year	Modality						fusion	Dataset	Accuracy
		Image	Audio	Text	EEG	SRI	Colour			
[16]	2015	√	√					Decision level	Fer+tfid	47.67
[17]	2017	√	√					Decision level	Recola	76.00
[18]	2018	√	√	√				Decision level	Cmu-mosei	49.10
[19]	2018	√	√	√				Feature level	Iemocap	77.60
[20]	2020				√			Feature level	Deap	89.53
[21]	2020	√	√	√				Hybrid	Iemocap	73.98
[22]	2021	√	√		√			FL,DL,HL	Ravdess, Eeg	78.75
[23]	2022	√	√	√	√			Weighted decision level	Combined customized dataset	93.00
[23]	2022	√	√	√	√			Weighted decision level	Real-world collected dataset	67.00
Proposed Approach	2025	√				√	√	Weighted decision level	Real-world collected dataset	79.00

4. DISCUSSION

Depression is among leading cause of disability in all age group globally and affects health care system severely. Millions of peoples affected and likely to be affected persons require psychological and / or clinical treatments. It more affected to woman as before and after pregnancy their hormones and body get changed. Teenagers are more emotional vulnerable and more connected to internet, social media, virtual world which make situations worst. If depression like mental health issues can be detected in initial stage it can cure with little care else situation may become worst.

This research is dedicated to such pre diagnostic self-automated tool which can produced reliable result by performing fusion of available classical methods. This research is a novel approach which analyzes classical Self Response Inventory (SRI) and Visual features of person without intervention of other person so one can be more secure and reliable result can be produced if tool is operated in neutral mode and dual approaches give significant result which is really boon for person who required clinical and /or psychological treatments.

There is future further research directions can be viewed which could be performed in near future for quality improvement of this automated tool. The model could focus on improving predictions for "Fear" "Sad" and "Neutral" where misclassifications are relatively high. To optimize the model's performance, especially for emotions like Fear, Sad, and Neutral, where misclassifications are significant, here are some detailed recommendations: First, if the participants' number could be increased performance of model will also improve. Second, quality of camera plays a major role and high-quality images contains visual features can retrieve specific information which further strengthen the visual behavioral analysis. Third, fusion of more modalities approaches like verbal features, social media text, EEG etc. could be improve the outcome.

Declaration

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- We have not any conflicting issues.

We have not published this work anywhere else.

REFERENCES

- [1] P. Ekman, Handbook of Cognition and Emotion, JohnWiley& Sons Ltd, 2005, pp. 45-60.
- [2] H. Ellgring, R. J. Eiser, K. R. Scherer, "Non-verbal Communication in Depression," Cambridge University Press, 2007.
- [3] American Psychiatric Association (5th edition, 2013). Diagnostic and statistical manual of mental disorders. Washington: DC.
- [4] Gupta R, Malandrakis N, Xiao B, Guha T, Van Segbroeck M, Black MP, Potamianos A, Narayanan SS (2014). Multimodal prediction of affective dimensions and depression in human-computer interactions. In International Audio/Visual Emotion Challenge and Workshop.
- [5] A. Pampouchidou, P.G. Simos, K. Marias, F. Meriaudeau, F. Yang, M. Pediatitis, M. Tsiknakis, "Automatic Assessment of Depression Based on Visual Cues: A Systematic Review," IEEE Transactions on Affective Computing, vol. 10, no. 4, pp. 445-470, 2019.
- [6] Komal Anadkat & Hiteishi M. Diwanji "Unimodal to Multimodal Emotion Recognition: A systematic Review" Test Engineering and Management "ISSN: 0193 4120, Volume 83 PP- 6423-6427 August 2020 (SCOPUS Indexed).
- [7] Alghowinem S, Goecke R, Wagner M, Parker G, Breakspear M (2013). Head pose and movement analysis as an indicator of depression. In Humaine Association Conference on Affective Computing and Intelligent Interaction, 283–288.
- [8] Alghowinem S, Goecke R, Wagner M, Parker G, Breakspear M (2013). Eye movement analysis for depression detection. In IEEE International Conference on Image Processing, 4220–4224.
- [9] Jeffrey M Girard, Jeffrey F Cohn, Mohammad H Mahoor, S Mohammad Mavadati, Zakia Hammal, and Dean P Rosenwald, "Nonverbal social withdrawal in depression: Evidence from manual and automatic analyses," Image and vision computing, pp. 641-647, 2014.
- [10] Internet resource: <https://www.verywellmind.com/colour-psychology-2795824>
- [11] Morales, M., Scherer, S., & Levitan, R, "A Cross-modal Review of Indicators for Depression Detection Systems," Proceedings of the Fourth Workshop on Computational Linguistics and Clinical Psychology -- From Linguistic Signal to Clinical Reality, 2017.
- [12] Y. Zhou, S. Scherer, D. Devault, J. Gratch, G. Stratou, L.-P. Morency, and J. Cassell, "Multimodal Prediction of Psychological Disorders: Learning Verbal and Nonverbal Commonalities in Adjacency Pairs,"

-
- 17th Workshop on the Semantics and Pragmatics of Dialogue. SEMDIAL, pp. 160-169, 2013.
- [13] R.Verma, "FER2013," Kaggle, 26-May-2018. [Online]. Available: <https://www.kaggle.com/datasets/deadskull7/fer2013>.
- [14] Pampouchidou, Anastasia, Kostas Marias, Manolis Tsiknakis, P. Simos, Fan Yang, and Fabrice Meriaudeau (2015). Designing a framework for assisting depression severity assessment from facial image analysis. In Signal and Image Processing Applications (ICSIPA), International Conference on, pp. 578-583, IEEE.
- [15] Patient Health Questionnaire-9, Kroenke, K., Spitzer, R. L., & Williams, J. B. W. (1999). Patient Health Questionnaire-9 (PHQ-9) [Database record]. APA PsycTests.
- [16] S. E. Kahou, X. Bouthillier, P. Lamblin, C. Gulcehre, V. Michalski, K. Konda, S. Jean, P. Froumenty, Y. Dauphin, N. Boulanger-Lewandowski, R. Chandias Ferrari, M. Mirza, D. Warde-Farley, A. Courville, P. Vincent, R. Memisevic, C. Pal, and Y. Bengio, "Emonets: Multimodal deep learning approaches for emotion recognition in video," *Journal on Multimodal User Interfaces*, vol. 10, no. 2, pp. 99-111, 2015.
- [17] P. Tzirakis, G. Trigeorgis, M. A. Nicolaou, B. W. Schuller, and S. Zafeiriou, "End to-End Multimodal Emotion Recognition Using Deep Neural Networks," *IEEE Journal of Selected Topics in Signal Processing*, vol. 11, no. 8, pp. 1301-1309, Dec. 2017, doi:10.1109/jstsp.2017.2764438.
- [18] S. Sahay, S. H. Kumar, R. Xia, J. Huang, and L. Nachman, "Multimodal relational tensor network for sentiment and emotion classification," *Proceedings of Grand Challenge and Workshop on Human Multimodal Language (Challenge-HML)*, 2018.
- [19] D. Hazarika, S. Poria, A. Zadeh, E. Cambria, L.-P. Morency, and R. Zimmermann, "Conversational memory network for emotion recognition in dyadic dialogue videos," *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers)*, 2018.
- [20] M. M. Hassan, Md. G. R. Alam, Md. Z. Uddin, S. Huda, A. Almogren, and G. Fortino, "Human emotion recognition using deep belief network architecture," *Information Fusion*, vol. 10.1016/j.inffus.2018.10.009. 51, pp. 10-18, Nov. 2019, doi: 21. S. Siriwardhana, A. Reis, R. Weerasekera, and S. Nanayakkara, "Jointly fine-tuning 'bert-like' self supervised models to improve multimodal speech emotion recognition," *Interspeech 2020*, 2020.
- [21] D. Priyasad, T. Fernando, S. Denman, S. Sridharan, and C. Fookes, "Attention driven fusion for multi-modal emotion recognition," *ICASSP 2020 - 2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2020.
- [22] J. Njoku, Angela C. Caliwag, W. Lim, S. Kim, H.-J. Hwang, and J.-W. Jeong, "Deep Learning Based Data Fusion Methods for Multimodal Emotion Recognition," *The Journal of Korean Institute of Communications and Information Sciences*, vol. 47, no. 1, pp. 79-87, Jan. 2022, doi: 10.7840/kics.2022.47.1.79.
- [23] Komal D. Anadkat, Dr. Hiteishi M. Diwanji & Dr. Shahid Modasiya "Effect Of Preprocessing In Human Emotion Analysis Using Social Media Status Dataset" *Reliability: Theory and Application* "ISSN 1932-2321, Volume 17 Issue 1 PP-67 March 2022 (SCOPUS Indexed).
- [24] Komal D. Anadkat & Dr. Hiteishi M. Diwanji "Effect of Activation Function in Speech Emotion Recognition On The Ravdess Dataset" *Reliability: Theory and Application* "ISSN 1932-2321, Volume 16 Issue 3 PP-63 September 2021 (SCOPUS Indexed).
- [25] Internet resources like: doc player.net, journalofbigdata., springeropen.com, deepai.org, arxiv.org, pubmed.ncbi.nlm.nih.gov
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Automatic mood detection tool: Self Response Inventory

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Abstract – Depression is a mood disorder in which negative mood of a person prolonged more than 2 weeks The World Health Organization list depression as major cause of disability. More than 370 million people suffer from it. Proper concern is not given to such burning issue globally. Psychological and clinical treatments are available but quality and availability of clinical professional associated to domain are limited. to resolve this issue an automated ML based approach is suggested for mood detection. Person can check its present mood automatically by its own at no cost. The accuracy of approach is above 90%. Person can repeat the test and if negative mood result continues then person can say to converge toward depressed mood.

Key Words: Depression, Positive mood, Negative mood, Psychology, PHQ-9, BDI, CES-D, MOS, SDDS-PC, QIDS, DMI-10, Mild Negative, Depressive disorder

1. INTRODUCTION

Depression is leading cause of disability globally in all age groups which severely affects the global health index. It is complex and an ongoing problem which may resolve with proper care but may reoccur via various risk factors. The medical community does not fully understand the causes of depression but mostly known various risk factors like environmental factors, psychological, social factors, financial factors, drug addictions change in genetic features, brain's neurotransmitter levels, accidental events like head major head injury and many more. Early detection plays a crucial role as by positive counseling, various physical and mental exercises like meditation and proper medication may resolved depression else situations become worst up to suicidal tendency. Depression can be detected through various behavioral symptoms and during clinical interview by medical expert but the rate of the affected person reach at right time with right medical professional is very low so many researchers from physiological, pattern matching, computer vision have tried to detect depression features from behavior verbal and nonverbal channels with help of various of machine learning algorithms under Artificial Intelligence domain. Neural Network has shown shows great potential to resolve this burning issue of human health care domain to serve mankind.

1.1 Clinical Interview

Psychological and clinical based interview to evaluate depression symptoms are carried out since last 60 years. Initially interviews were taken place in person or on

telephone lines where question is assessed on time scale of months. After decades scenario was changed with modifications of question and examination period was in weeks. In present situations where technology had made great impact on our life style the risk of depressed mood increase [6],[13],[14],[15],[16],[17],[28].

1.2 Audio Channel approach

Person having depressed mood speech can be identified so speech processing domain deal with such task and classify normal, mild depressed and major depressed person from vocal features [5],[11],[18],[19].

1.3 Visual Channel approach

Person having depressed mood can be identified from its visual features since long time person's expressions are recognized into seven prototypic class and they can further classify as positive and negative expression. Happy is positive emotion or expression where sad, disgust, angry, contempt are negative expressions. Surprise may lead to positive or negative expression according to the association of it with event [4],[7],[8],[9],[20],[21].

1.4 Social Media approach

In era of social networking technology person spare time more on screen so social media like Facebook, twitter, snap are identified person's mood and emotions so based on status, text message and updates like picture, snap person's data in which Text data in various levels and categorize with positive or negative broadly and much specific like emphatic, glad etc. databases for textual emotion analysis [18]. From uploaded pictures, emojis updated on various social media platforms person's mood behaviour can be examined.

1.5 Bio -sensor approach

There are various bio sensors are available to check the person's mental activity and associated parameters like EEG based approach physiological signals receive from brain are measured which are real time in nature and cannot suppress or hide like facial expressions, audio and textual emotions so it is more authentic and precise only drawback is the cost and complexity associate with this approach [18]. The result of such sensors is efficient only drawback is the cost and complexity of setup, evaluation and examination criteria in such modalities[19].

1.6 Multi-modal approach

Many contributors used fusion of above approaches called multi-modal data in which persons reflect their feelings through multiple channels [19], [20], [21]. Which are more accurate and reliable than focusing only on a single modal like audio, video, text, or EEG etc. [18],[22].

2. Classical Interview

In clinical approach person is assessed critically by medical mental health expert of psychology based on response of one-to-one interaction and real time observation by medical expert decision is made and psychological treatment and/or medication is applied [6]. Major problem with this approach is quantity of such assessment as person doesn't accept such mental health issues and because of social stigma they have tendency to conceal such issues so approximately 10% actually affected get benefits of this approach.

Hamilton Rating Scale for Depression (HRSD): popular as HAM-D which is MCQ type questionnaires which medical professional use for depression severity assessment [13].

Beck Depression Inventory (BDI): The BDI is 21 questions which are multiple option types self-report which calculate the severity of depression symptoms and feelings based on the response given [14].

Patient Health Questionnaires (PHQs): The PHQ-9 has nine questions about person's mood and daily activities like appetite, watching Television which helps Doctor come to a depression diagnosis [15]. The PHQ-2 asks the first two questions of the PHQ-9. Which is a screening test guide doctor for further processing.

Zung Self-Rating Depression Scale: It is again short surveys which identify depression levels [16].

Centre for Epidemiologic Studies-Depression Scale (CES-D): is a self-reported scale with 20 questions designed for caregivers to measure how often they have depression symptoms. A higher score can help doctor to identify risk level of depression [17].

By Analyzing all above approaches proposed System questionnaires are design in such a way that it fuse the physical, mental and cognitive health emotion with blend of colour psychology also to generate positive and negative mood classification task easier later negative mood further classified as mild, moderate and severe negative mood respectively.

Table -1: Comparative study of existing Approach

Comparison of existing Approach			
Tool with Year	Type	Questions	Scoring Levels / Severity
Beck Depression Inventory (BDI)1961	Self-Report	21	0-13: Min,14-19: Mild,20-28: Moderate,29-63: Severe
Beck Depression Inventory – Short Form (BDI-Short) 1978	Self-Report	13	0-4: Minimal, 5-7: Mild, 8-15: Moderate, ≥16: Severe
Center for Epidemiologic Studies Depression Scale(CES-D)1977	Self-Report	20	<16: Normal,16-26: Mild-Moderate, ≥27: Severe
Center for Epidemiologic Studies Depression Scale – Short Form (CES-D-Short)1997	Self-Report	10	<10: Normal10-14: Mild≥15: Severe
Medical Outcomes Study – Depression Scale (MOS) 1992	Self-Report	8	Low score: Normal, High score: Higher depression
Self-Diagnostic Depression Scale – Primary Care (SDDS-PC)1994	Self-Report	7	0-2: Normal3-4: Mild5-7: Severe
Patient Health Questionnaire – 9 (PHQ-9) 2001	Self-Report	9	0-4: Minimal,5-9: Mild10-14: Moderate,15-19: Mod-Severe20-27: Severe
Quick Inventory of Depressive Symptomatology (QIDS) 2003	Clinician/self	16	0-5: None6-10: Mild,11-15: Moderate16-20: Severe
Depression Measure Inventory – 10 (DMI-10) 2004	Self-Report	10	0-7: Normal,8-14: Mild15-20: Moderate>20: Severe
Proposed	Self-Report	21	0-4: Normal,5-9: Mild,10-14: Moderate,>15: Severe

Self –Response Inventory (S.R.I): Quiz based questionnaires approach in which person is required to respond quiz-based questions mainly deal with habit of food, sleep, rest concentration, decision making related to healthy life style on the best knowledge of truthfully based on response each question generate number and based on additive score mental health is decided. As mental health is depended primarily on our physical health which again rely on pattern of food, rest, exercise etc. and various psychological affective domain related aspects like communication, positive attitude towards life, concentration, decision making, colour selection depending on colour psychology where colour is used as tool for emotion identification not only as selection depending on psychology of colour [12] are truly responded represent true picture of our mental health in normal, mild negative, moderate negative and highly negative classes. The questions which are most important given twice weightage compare to others.

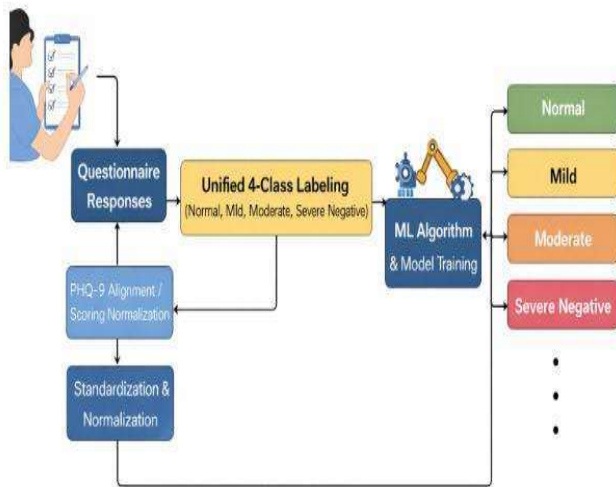


Fig -1: ML based model for S.R.I.

Data Analysis:

Total 150 person's response recorded on three options as Yes, No and not decided basis. Where 0-identifies not sure (neutral), Yes reflect the affirmation to question response while no reflect negative confirmation to the question. Questions are mixed with positive and negative form and mixed with generalized simple questions where person simply respond it and mood score is created automatically.

Table -2: Confusion Matrix of Proposed System

Confusion Matrix					
Predicted Actual →	Normal	Mild Negative	Moderate Negative	Severe Negative	Total
Normal ↓	85	3	2	0	90

Mild Negative	4	29	2	0	35
Moderate Negative	1	2	14	1	18
Severe Negative	0	1	1	5	7
Total	90	35	19	6	150

Table -3: Class- wise Performance of Proposed System

Confusion Matrix			
Class	Precision	Recall	F1-score
Normal	0.94	0.94	0.94
Mild Negative	0.83	0.83	0.83
Moderate Negative	0.74	0.78	0.76
Severe Negative	0.83	0.71	0.77
Average	0.84	0.82	0.83

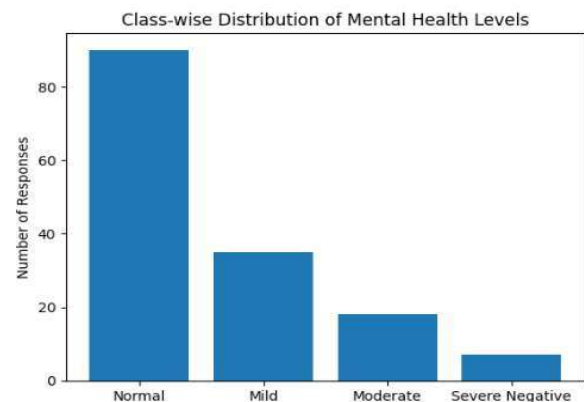


Chart -1: Bar graph of Proposed System classification

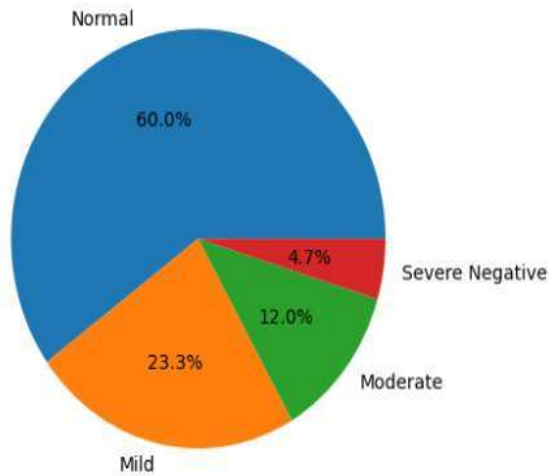


Chart -2: Pie chart of Proposed System Classification

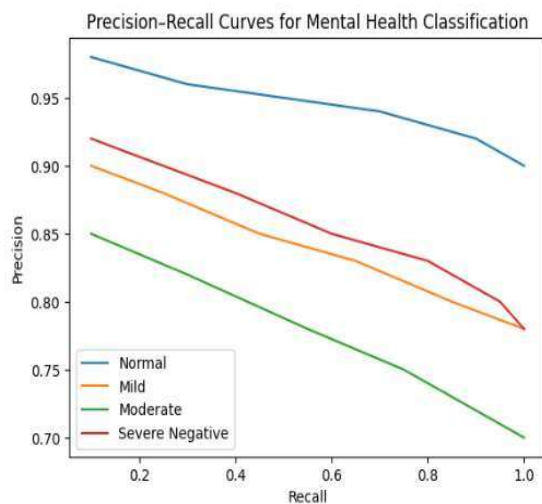


Chart -3: Precision-Recall Graph of Proposed System

Table -4: Mapping of Proposed System with PHQ-9

PHQ-9 range	Score Severity (PHQ-9)	Proposed System
0-4	Minimal	Normal Mood
5-9	Mild Depression	Mild Negative
10-14	Moderate Depression	Moderate Negative
>= 15	Moderately Severe Depression	Severe Negative Mood

Above mapping represent alignment of Proposed System with PHQ-9 which is clinically proven standard for depression which clearly reflect the clinical validity and acceptability of Proposed System as diagnosis tool in mental health care domain.

3. CONCLUSION

Number of researchers has contributed their work to identify depression which closely related with psychology, affective, computer and clinical domains so in real time it's a multi-challenging task. As domain start with Psychology, Computer Science and Clinical domain and last long to social domain the major key challenges are mentioned as under to map psychological domain to computer and validate it with behavioral/clinical predictions [22]. Human are expressive through verbal and nonverbal communication channels both channels are important to express feelings [3], [4]. Person can remain silent to suppress verbal communication and by fake expression or conceal expression can hide real scenario, biological sensor-based assessment of various biological parameters are complex to setup, execute and evaluation point of view and not user friendly. The person who is already in negative mind set not ready for any complex examination. In this approach no third person intervention or participation required person by own can check the mood automatically. All the modalities have its own pros and cons but classical approach of Questionnaires in automated version remain ultimate choice to validate mental health status. This automated mood detection tool which effectively identified mood via a set of quiz related to psychological, physical and general routine questionnaires person's mental health is estimated. If test continuously give negative mind state mood result the quiz can be repeated after 2 or 3 days as fresh version and evaluation of mood should carry out up to 2 weeks at various time like morning, afternoon, evening, night but if negative mood is reflected as outcome in all test results, then such person is advice to take care of mental health visit for clinical advice for further treatment.

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REFERENCES

[1] World Health Organization. The world health report (2003).shaping the future.

- [2] Mathers C., Boerma J, Fat D.(2008).The Global Burden of Disease. Update Geneva, Switzerland: WHO.
- [3] P. Ekman, Handbook of Cognition and Emotion, John Wiley & Sons Ltd, 2005, pp. 45-60.
- [4] H.Ellgring, R. J. Eiser, K. R. Scherer,"Non-verbal Communication in Depression," Cambridge University Press, 2007.
- [5] Yang Y, Fairbairn CE, Cohn JF (2013). Detecting depression severity from vocal prosody. IEEE Transactions on Affective Computing, 4:142-150.
- [6] MH, Ibrahim HM, Carmody TJ, Arnow B, Klein DN, Markowitz JC, Ninan PT, Kornstein S, Manber R, et al. (2003). The 16-item quick inventory of depressive symptomatology (qids), clinician rating (qids-c), and self-report (qids-sr). a psychometric evaluation in patients with chronic major depression. Biological psychiatry, 54(5):573-583.
- [7] Alghowinem S, Goecke R, Wagner M, Parker G, Breakspear M (2013). Head pose and movement analysis as an indicator of depression. In Humaine Association Conference on Affective Computing and Intelligent Interaction, 283-288.
- [8] Alghowinem S, Goecke R, Wagner M, Parker G, Breakspear M (2013). Eye movement analysis for depression detection. In IEEE International Conference on Image Processing, 4220-4224.
- [9] Girard JM, Cohn JF, Mahoor MH, Mavadati SM, Hammal Z, Rosenwald DP (2014). Nonverbal social withdrawal in depression: Evidence from manual and automatic analyses. Image and Vision Computing, 32:641-647.
- [10] Ooi KEB, Lech M, Allen NB (2013). Multichannel weighted speech classification system for prediction of major depression in adolescents. IEEE Transactions on Biomedical Engineering, 60:497-506.
- [11] Cummins N, Sethu V, Epps J, Krajewski J (2014). Probabilistic acoustic volume analysis for speech affected by depression. In Annual Conference of the International Speech Communication Association, 1238-1242.
- [12] Internet resource: <https://www.verywellmind.com/colour-psychology-2795824>
- [13] Hamilton M. A rating scale for depression (1960). Journal of neurology, neurosurgery, and psychiatry, 23(1): 56.
- [14] Beck AT, Steer RA, Ball R, Ranieri WF. (1996). Comparison of beck depression inventories-ia and-ii in psychiatric outpatients. Journal of personality assessment, 67(3):588-597.
- [15] Patient Health Questionnaire-9, Kroenke, K., Spitzer, R. L., & Williams, J. B. W. (1999). Patient Health Questionnaire-9 (PHQ-9) [Database record]. APA PsycTests.
- [16] Zung, WW (1965) A self-rating depression scale. Arch Gen Psychiatry 12, 63-70
- [17] Radloff, L.S. (1977). The CES-D Scale: a self-report depression scale for research in the general population. Applied Psychological Measurement, 1:385-401.
- [18] Komal D. Anadkat & Dr. Hiteishi M. Diwanji "Effect of Activation Function in Speech Emotion Recognition On The Ravdess Dataset" Reliability: Theory and Application "ISSN 1932-2321, Volume 16 Issue 3 PP-63 September 2021 (SCOPUS Indexed).
- [19] N.Cummins, J.Joshi, A.Dhall, V.Sethu, R.Goecke, J.Epps (2013, October). Diagnosis of depression by behavioural signals: a multimodal approach. AVEC'13: Proceeding of the 3rd ACM international workshop on Audio/Visual Emotion Challenges.
- [20] Jeffrey M Girard, Jeffrey F Cohn, Mohammad H Mahoor, S Mohammad Mavadati, Zakia Hammal, and Dean P Rosenwald, "Nonverbal social withdrawal in depression: Evidence from manual and automatic analyses," Image and vision computing, pp. 641-647, 2014.
- [21] Pampouchidou, Anastasia, Kostas Marias, Manolis Tsiknakis, P. Simos, Fan Yang, and Fabrice Meriaudeau (2015). Designing a framework for assisting depression severity assessment from facial image analysis. In Signal and Image Processing Applications (ICSIPA), International Conference on, pp. 578-583, IEEE.
- [22] Morales, M., Scherer, S., & Levitan, R, "A Cross-modal Review of Indicators for Depression Detection Systems," Proceedings of the Fourth Workshop on Computational Linguistics and Clinical Psychology -- From Linguistic Signal to Clinical Reality, 2017.
- [23] Kaya H, Salah AA (2013). Eyes whisper depression. In ACM International Workshop on Audio/Visual Emotion Challenge, 1-4.
- [24] Y. Zhou, S. Scherer, D. Devault, J. Gratch, G. Stratou, L.-P. Morency, and J. Cassell, "Multimodal Prediction of Psychological Disorders: Learning Verbal and Nonverbal Commonalities in Adjacency Pairs," 17th Workshop on the Semantics and Pragmatics of Dialogue. SEMDIAL, pp. 160-169, 2013.
- [25] Scherer S, Stratou G, Lucas G, Mahmoud M, Boberg J, Gratch J, Rizzo AS, Morency LP (2014). Automatic audiovisual behavior descriptors for psychological disorder analysis. Image and Vision Computing, 32:648-658.

[26] American Psychiatric Association (5th edition, 2013). Diagnostic and statistical manual of mental disorders. Washington: DC.

[27] Spitzer, R. L., Williams, J. B. W., Kroenke, K., Linzer, M., deGruy, F. V., Hahn, S. R., Brody, D., & Johnson, J. G. (1997). Utility of a new procedure for diagnosing mental disorders in primary care: The PRIME-MD 1000 study. **Journal of General Internal Medicine**, 12(7), 439–445. <https://doi.org/10.1046/j.1525-1497.1997.00076.x>

[28] Rush, A. J., Trivedi, M. H., Ibrahim, H. M., Carmody, T. J., Arnow, B., Klein, D. N., Markowitz, J. C., Ninan, P. T., Kornstein, S., Manber, R., Thase, M. E., Kocsis, J. H., & Keller, M. B. (2003). The 16-Item Quick Inventory of Depressive Symptomatology (QIDS), clinician rating (QIDS-C), and self-report (QIDS-SR): A psychometric evaluation in patients with chronic major depression. **Biological Psychiatry**, 54(5), 573–583. [https://doi.org/10.1016/S0006-3223\(02\)01866-8](https://doi.org/10.1016/S0006-3223(02)01866-8)

[29] Jiger P. Acharya, Dr. Milind S. Shah, (2025) Depression Detection System: A Systematic Review. *Journal of Neonatal Surgery*, 14(32s), 1486-1492.

[30] Jiger P. Acharya, Dr. Milind S. Shah, (2025) User Responsive Automatic Method for Real Time Depression Detection Using Deep Neural Network. *Journal of Neonatal Surgery*, 14(32s), 4286-4297.

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Depression Detection System: A Systematic Review

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ABSTRACT

Depression is mood disorders which result in severe disabling conditions affect person's ability to cope with routine life challenges. It may occur when person remain more than two weeks in negative state of mind continuously. Depending on severity depression is classified as mild, moderate and severe. The World health organization (WHO) list depression as major cause of suffering and disability worldwide more than 350 million people are affected and predict to be leading cause in 2020[1],[2]. Psychosocial and clinical treatments are available but persons have tendency to conceal it. Depression has observable behavioral symptoms related to affective and psychomotor domains which can be identified by human or machine. Classical approaches concerned to person's behavioral analysis and family observations during clinical interviews which are effective if it can be explicitly defined and precisely assessed while automatic system perform the said task effectively and open a new era for health care domain.

Keywords: Audio Video Emotion Challenge (AVEC), Visual features, Vocal features, Diagnostic and Statistical Manual of mental disorders (DSM), Deep Neural Network (DNN) etc.

1. INTRODUCTION

Depression is leading cause of disability globally in all age groups which severely affects the global health index. It is an ongoing problem which may resolve with proper care but may reoccur via various risk factors. The medical community does not fully understand the causes of depression but mostly known various risk factors like environmental factors, psychological, social factors, financial factors, drug addictions change in genetic features, brain's neurotransmitter levels, accidental events like head major head injury and many more. Early detection plays a crucial role as by positive counseling, various physical and mental exercises like meditation and proper medication may resolved depression else situations become worst up to suicidal tendency. Depression can be detected through various behavioral symptoms and during clinical interview by medical expert but the rate of the affected person reach at right time with right medical professional is very low so many researchers from physiological, pattern matching, computer vision have tried to detect depression features from behavior verbal and nonverbal channels with help of various of machine learning algorithms under Artificial Intelligence domain. Neural Network has shown shows great potential to resolve this burning issue of human health care domain to serve mankind.

2. METHODS

Human express their emotions through multiple channels which can be monitored for emotion analysis.[3],[4],[5]. There are many approaches like Clinical, Visual, Verbal, Colour psychology, Self Response clinical inventory, EEG etc. to determine the mental health of a person as mentioned below.

In clinical approach person is assessed critically by medical mental health expert of psychology based on response of one-to-one interaction and real time observation by medical expert decision is made and psychological treatment and/or medication is applied [6]. Major problem with this approach is quantity of such assessment as person doesn't accept such mental health issues and because of social stigma they have tendency to conceal such issues so approximately 10% actually affected get benefits of this approach.

In Visual channel in computer vision, pattern matching and image community detect depression features from behavior visual channels. Wager et al. [7] suggested that depression can be judge by head, pose movement of person and tendency of social withdrawal [8], [9] which can be judge from manual and automatic analysis. Cohn et al. [9] prove that during

depression verbal and nonverbal channels are affected significantly which can be identified during external observations.

In Audio based approach Ooi et al. [10] in 2013 present system which automatically measure audio parameters for prediction possibility of development of depression in near future which is very useful for identification of depression features in adolescents with use of a novel multichannel classification approach with classification accuracy of 73% in prospective screening and major work on verbal channel reported by [10] [11].

In Colour psychology-based approach reveals how various colours impact person's mood and so behaviors. It enlightens colour impact on person's emotional response based on age and cultural background etc. [12]. Major evidence in this emerging area is based on the feedback result of anecdotal, but domain expert has made a few important conclusions that how colour theory correlate with behaviors. In 2020 study that surveyed the emotional associations of 4598 persons from 30 countries and conclude that people commonly associate certain colours with specific emotions as below:

Table 1: Colour association with Emotion and Mood

Colour	Percentage	Emotions	Mood Category
White	51%	Sad	negative
White	43%	Relief	Positive
Red	68%	Love	Positive
Blue	35%	Relief	Positive
Green	39%	Contentment	negative
Yellow	52%	Joy	Positive
Purple	25%	Pleasant	Positive
Brown	36%	disgust	negative
Orange	44%	Joy	Positive
pink	50%	Love	Positive

Self –Response Inventory (S.R.I): Quiz based approach in which person is required to respond quiz based on the best knowledge of truthfully based on response each question generate number and based on additive score mental health is decided.

Hamilton Rating Scale for Depression (HRSD): popular as HAM-D which is MCQ type questionnaires which medical professional use for depression severity assessment [13].

Beck Depression Inventory (BDI): The BDI is 21 questions which are multiple option types self-report which calculate the severity of depression symptoms and feelings based on the response given [14].

Patient Health Questionnaires (PHQs): The PHQ-9 has nine questions about person's mood and daily activities like appetite, watching Television which helps Doctor come to a depression diagnosis [15]. The PHQ-2 asks the first two questions of the PHQ-9. Which is a screening test guide doctor for further processing.

Zung Self –Rating Depression Scale: It is again short surveys which identify depression levels [16].

Centre for Epidemiologic Studies-Depression Scale (CES-D): is a self-reported scale with 20 questions designed for caregivers to measure how often they have depression symptoms. A higher score can help doctor to identify risk level of depression [17].

In EEG based approach physiological signals receive from brain are measured which are real time in nature and cannot suppress or hide like facial expressions, audio and textual emotions so it is more authentic and precise only drawback is the cost and complexity associate with this approach [18].

In social media related approach data in which Text data in various levels and categorize with positive or negative broadly and much specific like emphatic, glad etc. databases for textual emotion analysis [18].

Many contributors used fusion of above in specific group called multi-modal data in which persons reflect their feelings through multiple channels [19], [20], [21]. Which are more accurate and reliable than focusing only on a single modal like audio, video, text, or EEG etc. [18],[22].Major research of said domain is as mentioned.

Table 2: Authors contribution of domain related research

Sr	Authors	Type	Dataset
1	Becker et al. (1994)	Audio/Video	Dementia Bank Database Reddit Self-reported
2	Valstaret al. (2013)	Audio/Video	AVEC 2013
3	Pradhan et al. (2014)	Text data	SemEval-2014 Task 7
4	Lieberman et al. (2013)	Text data	Crisis Text Line
5	Valstaretal. (2014)	Audio/Video	AVEC 2014
6	Gratch J et al. (2014)	Audio/Video	The Distress Analysis Interview Corpus
7	Valstaretal. (2016)	Audio/Video	AVEC 2016
8	Videbech (2016)	Audio/Video /Report	The Danish Depression Database
9	Yates et al. (2017)	Text data	Depression Diagnosis (RSDD) dataset
10	Garcia-Ceja et al. (2018)	Audio/Video	Depression
11	Anadkat et al. (2022)	Audio/Video/Social media text/EEG	FER2013, Ravdess, Kaggle's social media dataset, and EEG dataset

3. RESULTS/KEY OBSERVATIONS:

Visual as major channel for detection:

Face is the major channel of emotions indication. People reflect their feelings knowingly or unknowingly by their facial expression so face is considered as prime part of body for expression so based on this fact Ekman [3] categorize standard expression of six fundamental feelings along with Head orientation, posture and movement majorly use to recognize depression [7],[8],[24], [25].Girard et al [20] explore strong co-relation between visual direction and depression.

Table 3: List of major Visual Features for Behavior Detection

Features	Association with Facial Features
1	Eyelid opening /squinting movement
2	Outward appearance event with inconstancy with force
3	Head appearance with direction and deployment
4	Face movement
5	Pupil enlargement/inclination
6	Iris development
7	Grin force and term
8	Eye stare
9	Dismissal articulation/negative event
10	Mouth corner appearance

Below table indicate performances for various approaches

Table 4: Comparison of proposed methods with existing approach performance evaluation

Ref No.	Year	Modality						fusion	Dataset	Accuracy
		Image	Audio	Text	EEG	SRI	Colour			
[29]	2015	√	√					Decision level	Fer+tfd	47.67
[30]	2017	√	√					Decision level	Recola	76.00
[31]	2018	√	√	√				Decision level	Cmu-mosei	49.10
[32]	2018	√	√	√				Feature level	Iemocap	77.60
[33]	2020				√			Feature level	Deap	89.53
[34]	2020	√	√	√				Hybrid	Iemocap	73.98
[35]	2022	√	√	√	√			Weighted decision	Combined customized	93.00
[35]	2022	√	√	√	√			Weighted decision level	Real-world collected dataset	67.00

4. DISCUSSION

Human are expressive through verbal and nonverbal communication channels both channels are important to express feelings [3], [4]. Person can remain silent to suppress verbal communication and by fake expression or conceal expression can hide real scenario still researcher believes that facial expression is crucial input to present emotional status of person so psychologists try to map facial expressions to emotional states. When Person is feeling depression both verbal and nonverbal channel give strong indicators [22],[23],[24],[25]. Number of researchers has contributed their work to identify depression which closely related with psychology, affective, computer and clinical domains so in real time it's a multi-challenging task. As domain start with Psychology, Computer Science and Clinical domain and last long to social domain the major key challenges are mentioned as under to map psychological domain to computer and validate it with behavioral/clinical predictions [22].

- Psychology versus Computer Science: Psychology and Computer science have complexity and dependency in their specific domain.
 - Natural versus posed expression: There are vast differences in actual and acted expressions. The expression intensity, reality, and movement of muscles at macro and micro expressions play a major difference in expression execution.
 - Expression versus Emotion: Expression is movement of muscles while Emotions are related to heart. Expression can fabricate or acted but emotions are pure.
 - Static versus Dynamic analysis: Static image analysis is still image based while dynamic or video-based analysis has many frames which required being process.
 - Transitions among expressions and fusion expression: When transition of expressions occurs fixed out one expression is quite difficult and separate expression individually from fusion expression are quite challenging.
 - Variations in intensity level of facial expression: The intensity difference between expressions is subjective which is based on age, race, sex and ethnicity so take a decision globally quite challenging.
1. Deliberate versus spontaneous expression: some time execution of spontaneous expression differs from deliberate expression.
 2. Head orientation and scene complexity: Head is major region where expression execution happen so extract region

of Interest (ROI).

3. Neural Network limitation to train and execute Neural Network model we required large and variety amount of data which is a big challenge.
4. Spatial temporal setting during data collection: as in Image processing spatial temporal data play a crucial role and as it is very sensitive to light carefully data collection required in real time environment so standard metrics and requirement of wild implementation play a big role.
5. Emotional classes versus data classes in data labeling: Mapping of emotions classes and standard labeled data are big challenges.
6. Over fitting versus generalization: Balancing these two events is a quite difficult for any Neural Network.
7. Diagnostic criteria, clinical instruments, and performance metrics which have wide variety globally
8. Clinical specificity as many psychiatric and medical disorders-occur.
9. Temporal dynamics important in psychomotor retardation
10. Diversified large samples cultures, ethnicities, ages, and genders etc.

Depression is among leading cause of disability in each age group globally and affects health care system severely. Millions of affected and likely to be affected persons require psychological and/or clinical treatments. It more affected to woman as before and after pregnancy their hormones and body get changed. Teenagers are more emotional vulnerable and more connection to internet, social media, virtual world make situations worst. If depression can be detected in initial stage it can cure with little care else situation may become worst.

To all who have directly or indirectly motivated us to do little contribution to society by developing automated depression detection tool which effectively identified depression via a small set of quiz while attempting psychology related questionnaires person's mental health is estimated and while attempting quiz person's video is captured so visual and/ or vocal features are analyzed and matched with depression features if all result are inline Person is advice to take care of mental health visit for clinical advice for further treatment.

REFERENCES

- [1] World Health Organization. The world health report (2003). shaping the future.
- [2] Mathers C., Boerma J, Fat D.(2008).The Global Burden of Disease. Update Geneva, Switzerland: WHO.
- [3] P. Ekman, Handbook of Cognition and Emotion, John Wiley & Sons Ltd, 2005, pp. 45-60.
- [4] H. Ellgring, R. J. Eiser, K. R. Scherer, "Non-verbal Communication in Depression," Cambridge University Press, 2007.
- [5] Yang Y, Fairbairn CE, Cohn JF (2013). Detecting depression severity from vocal prosody. IEEE Transactions on Affective Computing, 4:142–150.
- [6] MH, Ibrahim HM, Carmody TJ, Arnov B, Klein DN, Markowitz JC, Ninan PT, Kornstein S, Manber R, et al. (2003). The 16-item quick inventory of depressive symptomatology (qids), clinician rating (qids-c), and self-report (qids-sr). a psychometric evaluation in patients with chronic major depression. Biological psychiatry, 54(5):573–583.
- [7] Alghowinem S, Goecke R, Wagner M, Parker G, Breakspear M (2013). Head pose and movement analysis as an indicator of depression. In Humaine Association Conference on Affective Computing and Intelligent Interaction, 283–288.
- [8] Alghowinem S, Goecke R, Wagner M, Parker G, Breakspear M (2013). Eye movement analysis for depression detection. In IEEE International Conference on Image Processing, 4220–4224.
- [9] Girard JM, Cohn JF, Mahoor MH, Mavadati SM, Hammal Z, Rosenwald DP (2014). Nonverbal social withdrawal in depression: Evidence from manual and automatic analyses. Image and Vision Computing, 32:641–647.
- [10] Ooi KEB, Lech M, Allen NB (2013). Multichannel weighted speech classification system for prediction of major depression in adolescents. IEEE Transactions on Biomedical Engineering, 60:497–506.
- [11] Cummins N, Sethu V, Epps J, Krajewski J (2014). Probabilistic acoustic volume analysis for speech affected by depression. In Annual Conference of the International Speech Communication Association, 1238–1242.
- [12] Internet resource: <https://www.verywellmind.com/colour-psychology-2795824>
- [13] Hamilton M. A rating scale for depression (1960). Journal of neurology, neurosurgery, and psychiatry, 23(1):56.

- [14] Beck AT, Steer RA, Ball R, Ranieri WF. (1996). Comparison of beck depression inventories-ia and-ii in psychiatric outpatients. *Journal of personality assessment*, 67(3):588–597.
- [15] Patient Health Questionnaire-9,Kroenke, K., Spitzer, R. L., & Williams, J. B. W. (1999). Patient Health Questionnaire-9 (PHQ-9) [Database record]. APA PsycTests.
- [16] Zung, WW (1965) A self-rating depression scale. *Arch Gen Psychiatry* 12, 63-70
- [17] Radloff, L.S. (1977). The CES-D Scale: a self-report depression scale for research in the general population. *Applied Psychological Measurement*, 1:385-401.
- [18] Komal D. Anadkat & Dr. Hiteishi M. Diwanji “Effect of Activation Function in Speech Emotion Recognition On The Ravdess Dataset” Reliability: Theory and Application “ISSN 1932-2321, Volume 16 Issue 3 PP-63 September 2021 (SCOPUS Indexed).
- [19] N.Cummins, J.Joshi, A.Dhall, V.Sethu, R.Goecke, J.Epps (2013, October). Diagnosis of depression by behavioural signals: a multimodal approach. AVEC’13: Proceeding of the 3rd ACM international workshop on Audio/Visual Emotion Challenges.
- [20] Jeffrey M Girard, Jeffrey F Cohn, Mohammad H Mahoor, S Mohammad Mavadati, Zakia Hammal, and Dean P Rosenwald, "Nonverbal social withdrawal in depression: Evidence from manual and automatic analyses," *Image and vision computing*, pp. 641-647, 2014.
- [21] Pampouchidou, Anastasia, Kostas Marias, Manolis Tsiknakis, P. Simos, Fan Yang, and Fabrice Meriaudeau (2015). Designing a framework for assisting depression severity assessment from facial image analysis. In *Signal and Image Processing Applications (ICSIPA)*, International Conference on, pp. 578-583, IEEE.
- [22] Morales, M., Scherer, S., & Levitan, R, "A Cross-modal Review of Indicators for Depression Detection Systems," *Proceedings of the Fourth Workshop on Computational Linguistics and Clinical Psychology — From Linguistic Signal to Clinical Reality*, 2017.
- [23] Kaya H, Salah AA (2013). Eyes whisper depression. In *ACM International Workshop on Audio/Visual Emotion Challenge*, 1–4.
- [24] Y. Zhou, S. Scherer, D. Devault, J. Gratch, G. Stratou, L.-P. Morency, and J. Cassell, "Multimodal Prediction of Psychological Disorders: Learning Verbal and Nonverbal Commonalities in Adjacency Pairs," *17th Workshop on the Semantics and Pragmatics of Dialogue. SEMDIAL*, pp. 160-169, 2013.
- [25] Scherer S, Stratou G, Lucas G, Mahmoud M, Boberg J, Gratch J, Rizzo AS, Morency LP (2014). Automatic audiovisual behavior descriptors for psychological disorder analysis. *Image and Vision Computing*, 32:648–658.
- [26] Lopez-Otero P, Docio-Fernandez L, Garcia-Mateo C (2014). A study of acoustic features for the classification of depressed speech. *Proceedings of the International Convention on Information and Communication Technology, Electronics and Microelectronics*, 1331–1335.
- [27] American Psychiatric Association (5th edition, 2013). *Diagnostic and statistical manual of mental disorders*. Washington: DC.
- [28] A Summarization of the Visual Depression Databases for Depression Detection 978-1-7281-7596-6/20 ©2020 IEEE explore
- [29] S. E. Kahou, X. Bouthillier, P. Lamblin, C. Gulcehre, V. Michalski, K. Konda, S. Jean, P. Froumenty, Y. Dauphin, N. Boulanger-Lewandowski, R. Chandias Ferrari, M. Mirza, D. Warde-Farley, A. Courville, P. Vincent, R. Memisevic, C. Pal, and Y. Bengio, “Emonets: Multimodal deep learning approaches for emotion recognition in video,” *Journal on Multimodal User Interfaces*, vol. 10, no. 2, pp. 99–111, 2015.
- [30] P. Tzirakis, G. Trigeorgis, M. A. Nicolaou, B. W. Schuller, and S. Zafeiriou, “End to-End Multimodal Emotion Recognition Using Deep Neural Networks,” *IEEE Journal of Selected Topics in Signal Processing*, vol. 11, no. 8, pp. 1301–1309, Dec. 2017, doi:10.1109/jstsp.2017.2764438.
- [31] S. Sahay, S. H. Kumar, R. Xia, J. Huang, and L. Nachman, “Multimodal relational tensor network for sentiment and emotion classification,” *Proceedings of Grand Challenge and Workshop on Human Multimodal Language (Challenge-HML)*, 2018.
- [32] D. Hazarika, S. Poria, A. Zadeh, E. Cambria, L.-P. Morency, and R. Zimmermann, “Conversational memory network for emotion recognition in dyadic dialogue videos,” *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers)*, 2018.
- [33] S. Siriwardhana, A. Reis, R. Weerasekera, and S. Nanayakkara, “Jointly fine-tuning ‘bert-like’ self supervised models to improve multimodal speech emotion recognition,” *Interspeech 2020*, 2020.
- [34] D. Priyasad, T. Fernando, S. Denman, S. Sridharan, and C. Fookes, “Attention driven fusion for multi-modal

emotion recognition,” ICASSP 2020 - 2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2020.

- [35] Komal D. Anadkat, Dr. Hiteishi M. Diwanji & Dr. Shahid Modasiya “Effect Of Preprocessing In Human Emotion Analysis Using Social Media Status Dataset” Reliability: Theory and Application “ISSN 1932-2321, Volume 17 Issue 1 PP-67 March 2022 (SCOPUS Indexed).
 - [36] A. Ashraf, T. S. Gunawan, F. D. A. Rahman, M. Kartiwi, N. Ismail and Ulfiah, "A Summarization of the Visual Depression Databases for Depression Detection," 2020 6th International Conference on Wireless and Telematics (ICWT), Yogyakarta, Indonesia, 2020, pp. 1-6, doi: 10.1109/ICWT50448.2020.9243625.
 - [37] Internet resources like: doc player.net, journal of bigdata., springeropen.com, deepai.org, arxiv.org, pubmed.ncbi.nlm.nih.gov
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APPENDICES

BLANK FORM WITH DEPRESSION INDICATOR

Appendix A:

Self Response Inventory (S.R.I.)

Sr	Question (Select option based on past 2-3 days experience)	Outcome	Yes	No	Not Decided
1	Have you got enough sleep?	Rest		1	
	Evaluates your physical well-being and rest. Adequate sleep is essential for health and productivity.				
2	Have you taken enough healthy food (in bf / lunch /dinner)?	Food		1	
	Assesses whether you are meeting your nutritional needs for energy and overall health.				
3	Have you done any exercise/yoga/workout?	Exercise		1	
	Reflects your physical activity levels, which are important for maintaining health, fitness, and mental well-being.				
4	Are you enjoying your daily routine?	Enjoyment		1	
	Indicates satisfaction and contentment with your daily life and habits.				
5	Can you select your clothes by yourself?	Decision		1	
	Measures independence and autonomy in decision-making and self-care.				
6	Can you prepare / suggest foods? (For bf / lunch /dinner)?	Selection/Creativity		1	
	Evaluates self-sufficiency in meal planning and preparation.				
7	Have you interacted with your family members to share your thoughts or feelings?	Sharing feelings		1	
	Assesses emotional connectivity and communication with loved ones.				
8	Are you comfortable communicating with your neighbors /colleagues/or friends?	Communication		1	
	Measures your social comfort and ability to engage with people in various settings.				
9	Do you spare some time to do your liking things?	Hobby /liking		1	
	Reflects your balance between responsibilities and personal enjoyment or hobbies.				
10	Can you read newspaper/books/articles easily?	Concentration		1	
	Evaluates cognitive function, literacy, and engagement with information.				
11	Can you watch TV/mobile/Movie easily?	Concentration		1	
	Measures ease of leisure activity and mental relaxation.				
12	Are you satisfied with your individual achievement/contribution to family/Society?	Self esteem		1	
	Reflects self-assessment of your accomplishments and your sense of purpose and fulfillment of your efforts and knowledge/Skills and attitude.				

Self Response Inventory (S.R.I.)

Y N N.D.

13	Do you have interest in things which appeal to you a lot previously?	Active Participation		1	
Examine personal interests and desires related to romantic/pleasure connections.					
14	Do you feel your life going smoothly?	Satisfaction		1	
Reflects your perception of life's trajectory and personal well-being.					
15	Do you feel tomorrow is better than present?	Optimistic		1	
Indicates optimism and hope for a better future.					
16	Do you feel you are unique, and no one can replace yourself?	Self-worth		1	
Reflects self-worth and a sense of individuality.					
17	Do you feel overburden with your study/work /responsibilities?	Stressless routine	1		
Whether you experience feelings of pressure, anxiety, or overwhelm due to your academic, professional, or personal duties.					
18	Do you agree after providing lots of efforts from your side almost everything is out of control?	in control situation	1		
if you ever feel like, despite putting in a lot of hard work and effort, things still aren't progressing as they should. It reflects a sense of frustration or helplessness,					
19	Do you feel frustrated or aloneness?	Helplessness	1		
Reflects feelings of frustration, helplessness, or burnout. The outcome of this question could reveal several underlying emotional or psychological states, such as: Frustration or Disappointment, Helplessness or Powerlessness, Burnout, Lack of Progress or Direction, Self-Doubt.					
20	Selection of Colour base on your mood from these: Black/Red/None	Colour Black:- 1 Red: None:			
Mood association with colour.					
21	Have you come across negative thoughts /suicidal thoughts?	Negative state mind	1		
Negativity					

Name:

Age :

Male / Female:

Phone no:

EMAIL:

Appendix B:

Self Response Inventory (S.R.I.)

NORMAL Mood

OR

NO DEPRESSION

Sr	Question (Select option based on past 2-3 days experience)	Outcome	Yes	No	Not Decided
1	Have you got enough sleep?	Rest	✓ 0		
	Evaluates your physical well-being and rest. Adequate sleep is essential for health and productivity.				
2	Have you taken enough healthy food (in bf / lunch /dinner)?	Food	✓ 0		
	Assesses whether you are meeting your nutritional needs for energy and overall health.				
3	Have you done any exercise/yoga/workout?	Exercise			✓
	Reflects your physical activity levels, which are important for maintaining health, fitness, and mental well-being.				
4	Are you enjoying your daily routine?	Enjoyment	✓ 0		
	Indicates satisfaction and contentment with your daily life and habits.				
5	Can you select your clothes by yourself?	Decision	✓ 0		
	Measures independence and autonomy in decision-making and self-care.				
6	Can you prepare / suggest foods? (For bf / lunch /dinner)?	Selection/Creativity	✓ 0		
	Evaluates self-sufficiency in meal planning and preparation.				
7	Have you interacted with your family members to share your thoughts or feelings?	Sharing feelings			✓
	Assesses emotional connectivity and communication with loved ones.				
8	Are you comfortable communicating with your neighbors /colleagues/or friends?	Communication	✓ 0		
	Measures your social comfort and ability to engage with people in various settings.				
9	Do you spare some time to do your liking things?	Hobby /liking	✓ 0		
	Reflects your balance between responsibilities and personal enjoyment or hobbies.				
10	Can you read newspaper/books/articles easily?	Concentration			✓
	Evaluates cognitive function, literacy, and engagement with information.				
11	Can you watch TV/mobile/Movie easily?	Concentration	✓ 0		
	Measures ease of leisure activity and mental relaxation.				
12	Are you satisfied with your individual achievement/contribution to family/Society?	Self esteem	✓ 0		
	Reflects self-assessment of your accomplishments and your sense of purpose and fulfillment of your efforts and knowledge/Skills and attitude.				

Self Response Inventory (S.R.I.)

13	Do you have interest in things which appeal to you a lot previously?	Active Participation		✓ 1	
	Examine personal interests and desires related to romantic/pleasure connections.				
14	Do you feel your life going smoothly?	Satisfaction		✓	
	Reflects your perception of life's trajectory and personal well-being.				
15	Do you feel tomorrow is better than present?	Optimistic			✓
	Indicates optimism and hope for a better future.				
16	Do you feel you are unique, and no one can replace yourself?	Self-worth		✓	
	Reflects self-worth and a sense of individuality.				
17	Do you feel overburden with your study/work /responsibilities?	Stressless routine		✓	
	Whether you experience feelings of pressure, anxiety, or overwhelm due to your academic, professional, or personal duties.				
18	Do you agree after providing lots of efforts from your side almost everything is out of control?	in control situation		✓ 1	
	if you ever feel like, despite putting in a lot of hard work and effort, things still aren't progressing as they should. It reflects a sense of frustration or helplessness,				
19	Do you feel frustrated or aloneness?	Helplessness		✓	
	Reflects feelings of frustration, helplessness, or burnout. The outcome of this question could reveal several underlying emotional or psychological states, such as: Frustration or Disappointment, Helplessness or Powerlessness, Burnout, Lack of Progress or Direction, Self-Doubt.				
20	Selection of Colour base on your mood from these: Black/Red/None	Colour Black: ✓ Red: None:		✓ 1	
	Mood association with colour.				
21	Have you come across negative thoughts /suicidal thoughts?	Negative state mind		✓	
	Negativity				

Name: HARSHAL SHAM

Age : 17

Male / Female: MALE

Phone no: 6352420191

EMAIL: harshalshah161@gmail-com

3/21

Harshal

Appendix C: Self Response Inventory (S.R.I.)

NEGATIVE MOOD

Sr	Question (Select option based on past 2-3 days experience)	Outcome	Yes	No	Not Decided
1	Have you got enough sleep?	Rest	☒	☐	☐
	Evaluates your physical well-being and rest. Adequate sleep is essential for health and productivity.				
2	Have you taken enough healthy food (in bf / lunch /dinner)?	Food	☒	☐	☐
	Assesses whether you are meeting your nutritional needs for energy and overall health.				
3	Have you done any exercise/yoga/workout?	Exercise	☒	☐	☐
	Reflects your physical activity levels, which are important for maintaining health, fitness, and mental well-being.				
4	Are you enjoying your daily routine?	Enjoyment	☒	☐	☐
	Indicates satisfaction and contentment with your daily life and habits.				
5	Can you select your clothes by yourself?	Decision	☒	☐	☐
	Measures independence and autonomy in decision-making and self-care.				
6	Can you prepare / suggest foods? (For bf / lunch /dinner)?	Selection/Creativity	☒	☐	☐
	Evaluates self-sufficiency in meal planning and preparation.				
7	Have you interacted with your family members to share your thoughts or feelings?	Sharing feelings	☒	☐	☐
	Assesses emotional connectivity and communication with loved ones.				
8	Are you comfortable communicating with your neighbors /colleagues/or friends?	Communication	☒	☐	☐
	Measures your social comfort and ability to engage with people in various settings.				
9	Do you spare some time to do your liking things?	Hobby /liking	☒	☐	☐
	Reflects your balance between responsibilities and personal enjoyment or hobbies.				
10	Can you read newspaper/books/articles easily?	Concentration	☒	☐	☐
	Evaluates cognitive function, literacy, and engagement with information.				
11	Can you watch TV/mobile/Movie easily?	Concentration	☒	☐	☐
	Measures ease of leisure activity and mental relaxation.				
12	Are you satisfied with your individual achievement/contribution to family/Society?	Self esteem	☒	☐	☐
	Reflects self-assessment of your accomplishments and your sense of purpose and fulfillment of your efforts and knowledge/Skills and attitude.				

Self Response Inventory (S.R.I.)

13	Do you have interest in things which appeal to you a lot previously?	Active Participation	✓ 0		
Examine personal interests and desires related to romantic/pleasure connections.					
14	Do you feel your life going smoothly?	Satisfaction	✓ 0		
Reflects your perception of life's trajectory and personal well-being.					
15	Do you feel tomorrow is better than present?	Optimistic	✓ 0		
Indicates optimism and hope for a better future.					
16	Do you feel you are unique, and no one can replace yourself?	Self-worth	✓ 0		
Reflects self-worth and a sense of individuality.					
17	Do you feel overburden with your study/work /responsibilities?	Stressless routine	✓ (1)		
Whether you experience feelings of pressure, anxiety, or overwhelm due to your academic, professional, or personal duties.					
18	Do you agree after providing lots of efforts from your side almost everything is out of control?	in control situation	✓ (1)		
if you ever feel like, despite putting in a lot of hard work and effort, things still aren't progressing as they should. It reflects a sense of frustration or helplessness,					
19	Do you feel frustrated or aloneness?	Helplessness	✓ (1)		
Reflects feelings of frustration, helplessness, or burnout. The outcome of this question could reveal several underlying emotional or psychological states, such as: Frustration or Disappointment, Helplessness or Powerlessness, Burnout, Lack of Progress or Direction, Self-Doubt.					
20	Selection of Colour base on your mood from these: Black/Red/None	Colour Black:- ✓ Red: None:	✓ (1)		
Mood association with colour.					
21	Have you come across negative thoughts /suicidal thoughts?	Negative state mind	✓ (1)		
Negativity					

Name: Bhunija Kamal R.

Age: 20

✓ Male / Female:

Phone no: 6351038594

EMAIL: bhuniyakgsu@gmail.com

Kamal

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MODERATE

Appendix D:

Self Response Inventory (S.R.I.)

NEGATIVE MOOD

Sr	Question (Select option based on past 2-3 days experience)	Outcome	Yes	No	Not Decided
1	Have you got enough sleep?	Rest		✓ (1)	
	Evaluates your physical well-being and rest. Adequate sleep is essential for health and productivity.				
2	Have you taken enough healthy food (in bf / lunch /dinner)?	Food	✓		
	Assesses whether you are meeting your nutritional needs for energy and overall health.				
3	Have you done any exercise/yoga/workout?	Exercise		✓ (1)	
	Reflects your physical activity levels, which are important for maintaining health, fitness, and mental well-being.				
4	Are you enjoying your daily routine?	Enjoyment		✓ (1)	
	Indicates satisfaction and contentment with your daily life and habits.				
5	Can you select your clothes by yourself?	Decision		✓ (1)	
	Measures independence and autonomy in decision-making and self-care.				
6	Can you prepare / suggest foods? (For bf / lunch /dinner)?	Selection/Creativity	✓		
	Evaluates self-sufficiency in meal planning and preparation.				
7	Have you interacted with your family members to share your thoughts or feelings?	Sharing feelings		✓ (1)	
	Assesses emotional connectivity and communication with loved ones.				
8	Are you comfortable communicating with your neighbors /colleagues/or friends?	Communication	✓		
	Measures your social comfort and ability to engage with people in various settings.				
9	Do you spare some time to do your liking things?	Hobby /liking		✓ (1)	
	Reflects your balance between responsibilities and personal enjoyment or hobbies.				
10	Can you read newspaper/books/articles easily?	Concentration	✓		
	Evaluates cognitive function, literacy, and engagement with information.				
11	Can you watch TV/mobile/Movie easily?	Concentration	✓		
	Measures ease of leisure activity and mental relaxation.				
12	Are you satisfied with your individual achievement/contribution to family/Society?	Self esteem		✓ (1)	
	Reflects self-assessment of your accomplishments and your sense of purpose and fulfillment of your efforts and knowledge/Skills and attitude.				

Self Response Inventory (S.R.I.)

13	Do you have interest in things which appeal to you a lot previously?	Active Participation	✓		
Examine personal interests and desires related to romantic/pleasure connections.					
14	Do you feel your life going smoothly?	Satisfaction		✓ (1)	
Reflects your perception of life's trajectory and personal well-being.					
15	Do you feel tomorrow is better than present?	Optimistic	✓	✗	
Indicates optimism and hope for a better future.					
16	Do you feel you are unique, and no one can replace yourself?	Self-worth	✓		
Reflects self-worth and a sense of individuality.					
17	Do you feel overburden with your study/work /responsibilities?	Stressless routine	✓ (1)		
Whether you experience feelings of pressure, anxiety, or overwhelm due to your academic, professional, or personal duties.					
18	Do you agree after providing lots of efforts from your side almost everything is out of control?	in control situation	✓ (1)		
if you ever feel like, despite putting in a lot of hard work and effort, things still aren't progressing as they should. It reflects a sense of frustration or helplessness,					
19	Do you feel frustrated or aloneness?	Helplessness	✓ (1)		
Reflects feelings of frustration, helplessness, or burnout. The outcome of this question could reveal several underlying emotional or psychological states, such as: Frustration or Disappointment, Helplessness or Powerlessness, Burnout, Lack of Progress or Direction, Self-Doubt.					
20	Selection of Colour base on your mood from these: Black/Red/None	Colour Black:- ✓ (1) Red: None:			
Mood association with colour.					
21	Have you come across negative thoughts /suicidal thoughts?	Negative mind state	✓ (1)		
Negativity					

Name: Mansa

Age : 14

Male / Female:

Phone no: 9054118509 EMAIL: jignaacharya46@gmail.com

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Appendix E: Self Response Inventory (S.R.I.)

NEGATIVE MOOD

Sr	Question (Select option based on past 2-3 days experience)	Outcome	Yes	No	Not Decided
1	Have you got enough sleep?	Rest		✓ (1)	
	Evaluates your physical well-being and rest. Adequate sleep is essential for health and productivity.				
2	Have you taken enough healthy food (in bf / lunch /dinner)?	Food		✓ (1)	
	Assesses whether you are meeting your nutritional needs for energy and overall health.				
3	Have you done any exercise/yoga/workout?	Exercise		✓ (1)	
	Reflects your physical activity levels, which are important for maintaining health, fitness, and mental well-being.				
4	Are you enjoying your daily routine?	Enjoyment		✓ (1)	
	Indicates satisfaction and contentment with your daily life and habits.				
5	Can you select your clothes by yourself?	Decision	✓		
	Measures independence and autonomy in decision-making and self-care.				
6	Can you prepare / suggest foods? (For bf / lunch /dinner)?	Selection/Creativity		✓ (1)	
	Evaluates self-sufficiency in meal planning and preparation.				
7	Have you interacted with your family members to share your thoughts or feelings?	Sharing feelings			
	Assesses emotional connectivity and communication with loved ones.				
8	Are you comfortable communicating with your neighbors /colleagues/or friends?	Communication		✓ (1)	
	Measures your social comfort and ability to engage with people in various settings.				
9	Do you spare some time to do your liking things?	Hobby /liking		✓ (1)	
	Reflects your balance between responsibilities and personal enjoyment or hobbies.				
10	Can you read newspaper/books/articles easily?	Concentration			
	Evaluates cognitive function, literacy, and engagement with information.				
11	Can you watch TV/mobile/Movie easily?	Concentration	✓		
	Measures ease of leisure activity and mental relaxation.				
12	Are you satisfied with your individual achievement/contribution to family/Society?	Self esteem		✓ (1)	
	Reflects self-assessment of your accomplishments and your sense of purpose and fulfillment of your efforts and knowledge/Skills and attitude.				

Self Response Inventory (S.R.I.)

Y N ND.

13	Do you have interest in things which appeal to you a lot previously?	Active Participation		✓ ①	
Examine personal interests and desires related to romantic/pleasure connections.					
14	Do you feel your life going smoothly?	Satisfaction		✓ ①	
Reflects your perception of life's trajectory and personal well-being.					
15	Do you feel tomorrow is better than present?	Optimistic		✓ ①	
Indicates optimism and hope for a better future.					
16	Do you feel you are unique, and no one can replace yourself?	Self-worth		✓ ①	
Reflects self-worth and a sense of individuality.					
17	Do you feel overburden with your study/work/responsibilities?	Stressless routine		✓	
Whether you experience feelings of pressure, anxiety, or overwhelm due to your academic, professional, or personal duties.					
18	Do you agree after providing lots of efforts from your side almost everything is out of control?	in control situation		✓ ①	
if you ever feel like, despite putting in a lot of hard work and effort, things still aren't progressing as they should. It reflects a sense of frustration or helplessness,					
19	Do you feel frustrated or aloneness?	Helplessness		✓ ①	
Reflects feelings of frustration, helplessness, or burnout. The outcome of this question could reveal several underlying emotional or psychological states, such as: Frustration or Disappointment, Helplessness or Powerlessness, Burnout, Lack of Progress or Direction, Self-Doubt.					
20	Selection of Colour base on your mood from these: Black/Red/None	Colour			
		Black:- ✓ ①			
		Red:			
		None:			
Mood association with colour.					
21	Have you come across negative thoughts /suicidal thoughts?	Negative state	mind	✓ ①	
Negativity					

Name: Bhavin

Age: 49 yrs

Male / Female: Male

Phone no: 9978921248 EMAIL:

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Self - Response Inventory (S.R.I.)

Sr	Question (Selection based on past 2-3 days experience)	Outcome	Yes	No	Not Decide
1	Have you got enough sleep?	Rest			
	Evaluates your physical well-being and rest. Adequate sleep is essential for health and productivity.				
2	Have you taken enough healthy food(in bf / lunch /dinner)?	Food			
	Assesses whether you are meeting your nutritional needs for energy and overall health.				
3	Have you done any exercise/yoga/workout?	Exercise			
	Reflects your physical activity levels, which are important for maintaining health, fitness, and mental well-being.				
4	Are you enjoying your daily routine?	Enjoyment			
	Indicates satisfaction and contentment with your daily life and habits.				
5	Can you select your clothes by yourself?	Decision			
	Measures independence and autonomy in decision-making and self-care.				
6	Can you prepare/suggest foods?(For bf / lunch /dinner)?	Selection/Creativity			
	Evaluates self-sufficiency in meal planning and preparation.				
7	Have you interacted with your family members to share your thoughts or feelings?	Sharing feelings			
	Assesses emotional connectivity and communication with loved ones.				
8	Are you comfortable communicating with your neighbors /colleagues/or friends?	Communication			
	Measures your social comfort and ability to engage with people in various settings.				
9	Do you spare some time to do your liking things?	Hobby/liking			
	Reflects your balance between responsibilities and personal enjoyment or hobbies.				
10	Can you read newspaper/books/articles easily?	Concentration			
	Evaluates cognitive function, literacy, and engagement with information.,				
11	Can you watch TV/mobile/Movie easily?	Concentration			
	Measures ease of leisure activity and mental relaxation.				
12	Are you satisfied with your individual achievement /contribution to family/Society?	Self- esteem			
	Reflects self-assessment of your accomplishments and your sense of purpose and fulfillment of your efforts and knowledge/Skills and attitude.				

Self - Response I

Sr	Question(Selectoptionbasedonpast2-3 days experience)				
13	Do you have interest in things which appeal to you a lot previously?	Active Participation			
	Examine personal interests and desires related to pleasure connections.				
14	Do you feel your life going smoothly?	Satisfaction			
	Reflects your perception of life's trajectory and personal well-being.				
15	Do you feel tomorrow is better than present?	Optimistic			
	Indicates optimism and hope for a better future.				
16	Do you feel you are unique, and no one can replace yourself?	Self-worth			
	Reflects self-worth and a sense of individuality.				
17	Do you feel overburden with your study/work /responsibilities?	Stressful routine			
	Whether you experience feelings of pressure, anxiety, or overwhelm due to your academic, professional, or personal duties.				
18	Do you agree after providing lots of efforts from your side almost everything is out of control?	Out of control situation			
	If you ever feel like, despite putting in a lot of hard work and effort, things still aren't progressing as they should. It reflects a sense of frustration or helplessness.				
19	Do you feel frustrated or aloneness?	Helplessness			
	Reflects feelings of frustration, helplessness, or burnout. The outcome of this question could reveal several underlying emotional or psychological states, such as: Frustration or Disappointment, Helplessness or Powerlessness, Burnout, Lack of Progress or Direction, Self-Doubt.				
20	Selection of Colour base on your current mood: Black, Red, None Select any one from above and mark tick.	Colourpsychology Black: Red: None:			
	Mood association with colour.				
21	Have you come across negative thoughts / Suicidal thoughts?	Negative mind state			
	Negativity				

I am ready to share this response for Academic Research purpose. SIGN:

Name: Dr. Shetal M. Raj

Age: , Male/Female:

Phone no:

EMAIL:



Very useful & appropriate to come to conclusion -
Shetal

Self - Response Inventory (S.R.I.)

Sr	Question (Selection based on past 2-3 days experience)	Outcome	Yes	No	Not Decided
1	Have you got enough sleep?	Rest			
	Evaluates your physical well-being and rest. Adequate sleep is essential for health and productivity.				
2	Have you taken enough healthy food(in bf / lunch /dinner)?	Food			
	Assesses whether you are meeting your nutritional needs for energy and overall health.				
3	Have you done any exercise/yoga/workout?	Exercise			
	Reflects your physical activity levels, which are important for maintaining health, fitness, and mental well-being.				
4	Are you enjoying your daily routine?	Enjoyment			
	Indicates satisfaction and contentment with your daily life and habits.				
5	Can you select your clothes by yourself?	Decision			
	Measures independence and autonomy in decision-making and self-care.				
6	Can you prepare/suggest foods?(For bf / lunch /dinner)?	Selection/Creativity			
	Evaluates self-sufficiency in meal planning and preparation.				
7	Have you interacted with your family members to share your thoughts or feelings?	Sharing feelings			
	Assesses emotional connectivity and communication with loved ones.				
8	Are you comfortable communicating with your neighbors /colleagues/or friends?	Communication			
	Measures your social comfort and ability to engage with people in various settings.				
9	Do you spare some time to do your liking things?	Hobby/liking			
	Reflects your balance between responsibilities and personal enjoyment or hobbies.				
10	Can you read newspaper/books/articles easily?	Concentration			
	Evaluates cognitive function, literacy, and engagement with information.				
11	Can you watch TV/mobile/Movie easily?	Concentration			
	Measures ease of leisure activity and mental relaxation.				
12	Are you satisfied with your individual achievement /contribution to family/Society?	Self- esteem			
	Reflects self-assessment of your accomplishments and your sense of purpose and fulfillment of your efforts and knowledge/Skills and attitude.				



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The assessment tool (S.R.I) used in this research has been derived from prepared existing tools. However, the limitation of this tool is that it has not been validated in a clinical sample. Clinical validation would increase confidence in the results of the present study.

Dr. Shermal Patel
6-53888