RECRUITMENT AND SELECTION PREDICTION IN THE CAMPUS PLACEMENT THROUGH MACHINE LEARNING

A Synopsis of Thesis

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1. Title of the Thesis and Abstract

1.1 Title of the Thesis

"RECRUITMENT AND SELECTION PREDICTION IN THE CAMPUS PLACEMENT THROUGH MACHINE LEARNING"

1.2 Abstract

Recruitment and selection are essential components of human resource management, significantly influencing the makeup of an organization's workforce. Traditional campus recruitment methods often focus heavily on academic performance and aptitude tests, frequently overlooking important factors like practical skills, co-curricular achievements, and evaluations from recruiters. This error can lead to the exclusion of potentially strong candidates who have relevant industry skills.

To make the hiring process better, we can use a variety of machine learning models like Boosting, Random Forest, Decision Trees, and Logistic Regression, SVM and many other classification algorithm.

This study emphasizes the importance of a structured, data-driven approach while also highlighting the limitations of traditional recruiting methods. By harnessing the power of machine learning, employers can refine their hiring processes, leading to a more thorough and fair assessment of candidates. This research not only enhances human resource management by providing a flexible and scalable way to boost hiring success but also opens the door for future studies to explore deep learning techniques and adaptive learning models to further improve candidate selection.

2. A Brief Description on the State of the Art of the Research Topic

Hiring and picking employees play a key role in managing a workforce, and they have a big impact on who ends up working for a company. In the past, college campus recruiting has tended to look at grades and test scores often not paying enough attention to other important things like hands-on skills, activities outside of class, and how recruiters feel about candidates. This means some promising job seekers with real-world know-how might not get a chance to show what they can do. To tackle these problems, this study suggests a machine learning method based on probability to spot the top applicants. It looks at hiring info from about 60 IT firms and checks 27 key points, like grades, tech know-how, projects, certificates, and personal traits. The research uses different machine learning tools such as Logistic Regression, Decision Trees, Random Forest, and Boosting, to make the hiring process better.

2.1 Motivation

The main motivation behind our research work for the requirement and selection prediction in the campus placement are:

a. Importance of the Campus placement

- Bridges the gap between the academia and the Industry.
- Providing the early career opportunities to the students
- Helps companies to select skilled fresher

b. Challenges in the traditional Placement Processes

- Dependence of the companies on the academic performance and skill tests.
- Limited assessment of the practical skills and the real world solving abilities
- Mismatch between the preparedness of the student and the industry requirement

c. Role of Machine Learning in the Placement Prediction

- **Supervised Learning models:** Logistic regression, Decision Trees, Random Forest, K- Nearest Neighbours.
- **Deep Learning Models:** Artificial Neural Networks (ANN).
- **Probabilistic Approaches:** Logistic Regression, Bayesian Classifiers for eligibility prediction.

d. Key Parameters for the companies placement prediction

- Academic records (CGPA, subject-wise performance).
- Technical skills and programming proficiency.
- Project work, research experience, and internships.
- Aptitude and problem-solving ability.
- Soft skills, communication, and teamwork.
- Industry-specific certifications and extracurricular activities.

e. Benefits for Institutions and Companies

- Institutions can personalize training programs to enhance employability.
- Companies can enhance their recruitment efforts by implementing a candidate selection process that relies on data.
- This approach minimizes bias in hiring by taking into account a wide range of factors.

f. Enhancement of the placement Strategies

- Identification of the additional parameters important for the recruiters.
- Aligning academic curricula with industry requirements.
- Helping students with personalized career advice and skill development strategies.

2.2 Challenges

a. Data Quality and Availability [1] [2]

- Incomplete or inconsistent student records, including academic performance, after-school activities, and work experience, have an impact on how predictions can be made.
- College using different ways to gather information make it hard to create a standard approach.
- What's more, worries about keeping personal details private make it tough to get full student profiles, which makes it harder to train models well.

b. Bias in Machine Learning Models [6]

- Old placement data might favour students from certain backgrounds, schools, or areas. When AI systems learn from biased info, they can widen existing gaps putting some students at a disadvantage.
- To ensure fair predictions, you need to use ways to cut down bias. However, putting these ways into action isn't a walk in the park.

c. Dynamic Industry Requirements [3] [4]

- The job market trends are constantly shifting, which means that models need to be updated regularly.
- Skills that are in demand, such as AI and cloud computing, change over time, rendering older training data less useful.
- Moreover, various industries and companies have their own specific hiring criteria, making it difficult to create a one-size-fits-all prediction model.

d. Algorithm Selection and Performance [1] [5]

- Not every machine learning algorithm is the best fit for every dataset; the choice depends on the specific traits of the data.
- Certain models, like deep learning, demand significant computing resources, which can lead to high implementation costs.

- Striking a balance between prediction accuracy, interpretability, and computational efficiency can be quite challenging.

e. Interpretability and Trust in Predictions [5] [6]

- Complex machine learning models, such as neural networks and ensemble methods, often function as "black boxes," which makes it challenging to understand their decision-making processes.
- This lack of clarity can lead to scepticism among recruiters and students regarding placement predictions.
- While creating explainable solutions can introduce additional complexity, it is essential for gaining acceptance and trust in these technologies.

f. Scalability and Customization [2] [3]

Placement criteria differ among universities, which complicates the application of a uniform model across institutions. Adapting to various student profiles and job markets necessitates flexible machine learning frameworks. Additionally, scaling models to handle large datasets raises demands for computational power and resources.

g. Real-World Implementation Challenges [4] [6]

Many institutions may be hesitant to shift from traditional placement methods to AI-driven approaches. Limitations in infrastructure, such as a lack of machine learning expertise and computational resources, can impede this transition. Additionally, regular retraining of models is necessary to keep up with changing hiring trends, which increases the maintenance workload.

h. Mismatch Between Predictions and Actual Hiring Decisions [1] [3] [5]

- Companies take into account more than just machine learning predictions; they also look at cultural fit and behavioural assessments.
- Candidates who may have lower predicted scores can still land jobs thanks to their soft skills or networking abilities.
- It's essential to ensure that machine learning models enhance, rather than substitute, human judgment.

2.3 Literature Review

1. Maximizing Campus Placement through Machine Learning [1]

This study explores the use of Machine Learning (ML) algorithms—Naïve Bayes, Random Forest, and Decision Tree—to predict student campus placements. By analyzing key factors, ML helps forecast job placement outcomes, aiding institutions in supporting students effectively.

2. Campus Placements Prediction & Analysis using Machine Learning [2]

The target is to analyse student's placement data of last year and use it to determine the probability of campus placement of the present students. For they have experimented with four different machine learning algorithms i.e. Logistic Regression, Decision Tree, K Nearest Neighbours and Random Forest.

3. Campus Placement Prediction using Machine Learning [3]

A campus placement prediction system is developed using supervised machine learning, particularly logistic regression, to assess a student’s likelihood of securing a job. It analyses academic records, test results, and past student data to enhance prediction accuracy. This helps students improve skills and assists institutions in optimizing placement strategies.

4. A Probabilistic Machine Learning Approach for Eligible Candidate Selection [6]

Proposed the system which helps the company to shortlist the candidates according to the candidate's CGPA, projects completed, area of interest, research work, experience etc. Since the recruiting process for the appropriate candidate requires many processes, so with the help of Naive Bayes Classifier author proposed a system which shortlists the applicant where parameters for the criteria can be changed according to the need. According to the author's result there may be chances where a candidate having high CGPA is not eligible .Whereas a candidate with low CGPA is eligible for a job.

5. Predicting Student Satisfaction in Emergency Remote Learning (ERL) [7]

This study explored the main factors influencing student satisfaction (N = 425) with ERL at a self-funded university in Hong Kong, utilizing Moodle and Microsoft Teams. When comparing various regression and machine learning models, elastic net regression demonstrated the highest accuracy, explaining 65.2% of the variance.

6. Educational Data Mining for Student Performance and Retention [8]

Educational Data Mining (EDM) improves learning by utilizing machine learning (ML) and data mining to assess student data. Today's universities encounter difficulties in assessing student performance, forecasting dropouts, and applying intervention strategies. A systematic review conducted from 2009 to 2021 showed that ML techniques are commonly employed for:

- Identifying students at risk and predicting dropouts.
- Examining institutional databases and online learning platforms to enhance outcomes.
- The findings indicate that predictions driven by ML contribute to reducing dropout rates and boosting student success.

7. Dynamic Job-Shop Scheduling Using Deep Reinforcement Learning [9]

The Job-Shop Scheduling Problem (JSP) focuses on determining the order in which jobs are processed in smart manufacturing, taking into account uncertainties such as machine breakdowns and the need for rework. Traditional scheduling methods often struggle to adapt, requiring significant rework whenever conditions change, which results in high time complexity.

To tackle this issue, a new dynamic scheduling method based on deep reinforcement learning (DRL) is introduced, employing proximal policy optimization (PPO) to handle the growing complexity of state and action spaces. Experimental results indicate that this method performs comparably to traditional approaches while providing adaptive and real-time scheduling capabilities.

Table 1: Various other studies for the Selection prediction and Campus selection

Ref	Scheduling Type	Features/Metric	Approach	Data Set	Accuracy
[10]	Placement Analysis	Student skill levels, university criteria, placement system assessments	Proposed: Logistic Regression, KNN, Gradient Boosting Classifier	Placement Data	Comparative analysis for optimal classificatio n method
[11]	Placement Analysis	Student details, dropout identification,	Decision Tree Algorithms (ID3,	Placement data from Dr. N.G.P. Arts and	ID3: 95.33%

		placement prediction	CHAID, C4.5)	Science College	
[12]	Placement Predictor	University scores, placement tests, skill assessment	Machine Learning: Classification Methods	University & Placement Management System Data	Varies by Algorithm
[13]	Placement Prediction	University scores, placement tests, domain expertise, outliers handling	Logistic Regression, SVM, KNN, Decision Tree, Random Forest, Voting Classifier	Institute Placement Data	78% (XGBoost, AdaBoost)
[23]	Batch Scheduling	GPA, Attendance, Study Hours	Random Forest	University Database	85%
[24]	Multi-class Grant Prediction	Expense, Score, Dormitory Activity, Book Loans	Ensemble Learning with Gradient Boosting, Random Forest, AdaBoost, SVM	10,885 students' daily behavior data	95.45 %
[26]	Criterion-Related Validity, Range Restriction Correction	Meta-Analysis of Personnel Selection Procedures	Meta-Analytic Review with Revised Range Restriction Correction	Prior Meta-Analyses on Predictor–Criterion Relationships	Reduced by .10–.20 points
[27]	Student Performance Prediction, Classification	UCI Machinery Student Performance Dataset	Machine Learning (Naïve Bayes, ID3, C4.5, SVM)	Evaluated on accuracy & error rate	-
[29]	Predictive	Career Counselling, Academic & Employability Analysis	Naïve Bayes, Logistic Regression, Decision Tree, SVM,	Educational dataset for job placements & skilling	Recall: 91.2%, F-Measure: 90.7% (Naïve Bayes)

			KNN, Ensemble		
[31]	Predictive	Assessment scores, engagement intensity, clickstream data, time-dependent variables	Random Forest, etc	Online learning platform data	91% (max)
[32]	Student Performance Prediction	Personal, academic, and behavioural features	Data Pre-processing, Factor Analysis, Machine Learning (Support Vector Regression - Linear)	Questionnaire-based survey & academic records from a technical institution in India	Superior prediction with SVR (Linear)

3. Problem Definition

The present campus hiring process focuses predominantly on academic merit and aptitude tests but lacks a holistic approach, which leads to missing out on talented students. By giving significant weight to academic marks and ignoring crucial elements such as co-curricular accomplishments and live assessments by recruiters, we lose sight of candidates who may excel outside of traditional academic metrics. It's therefore essential to adopt a systematic, data-driven approach to build a fair and efficient selection process.

4. Objective of the study and Scope of the work

The objective of this research is to enhance the campus recruitment process with the implementation of an organized, data-based system that ensures equitable and efficient selection of candidates. This is done through the process of attracting high-potential candidates by considering a broader perspective of assessment criteria other than academic achievement. The research aims to synchronize recruitment strategies with industry demands, making suggestions based on candidates' competences and skills. Besides this, it focuses on building a holistic recruitment architecture that integrates co-curricular efforts and in-app assessments. Transparency in the process of selection remains a top focus area with a goal of developing improved talent detection and increased results in hiring.

This research aims to revolutionize the traditional campus recruitment process by adopting a data-driven and comprehensive approach. The goal is to close the gap between academic performance and industry expectations by using various evaluation criteria, such as co-curricular achievements, real-time assessments from recruiters, and skill-based recommendations.

Scope

1. **Candidate Sourcing:** Finding high-quality candidates through a systematic selection process.
2. **Industry Alignment:** Making sure recruitment strategies keep pace with changing industry needs.
3. **Skill-Based Recommendations**: Utilizing data analytics to connect candidates with appropriate job roles.
4. **Holistic Recruitment:** Considering both academic and non-academic factors for a thorough evaluation.
5. **Transparency and Fairness:** Creating a standardized and impartial selection framework to enhance talent recognition.

5. Contribution to the thesis

This research presents a recruitment framework that leverages data and AI to revolutionize the conventional campus placement process. The key contributions of the study are detailed as follows:

5.1. Ethical Hiring & Bias Reduction System

Encourages a diverse and merit-based hiring process, ensuring equal opportunities for all students. Minimizes recruitment bias by applying an objective, data-driven selection framework.

5.2. Smart Internship-to-Job Pipeline

Allows companies to recruit proven talent by assessing candidates through real-world projects instead of relying solely on standardized tests.

5.3. AI-Powered Adaptive Assessment Engine

Continuously updates assessment criteria to match changing industry needs, ensuring students are evaluated on both current and future skill requirements.

5.4. Role-Specific Dynamic Scoring Model

Guarantees that companies receive candidates with the appropriate mix of skills tailored to specific job roles, rather than just generic test scores

5.5. Better Alignment between Education and Industry

Students receive training in skills that are directly relevant to what industries need. Colleges have the ability to update their curricula based on immediate feedback from the industry.

5.6. Promotes Lifelong Learning

Students are encouraged to continuously enhance their skills in response to changing industry demands.

5.7. Encourages Holistic Development

There is a strong emphasis on soft skills, cultural fit, and problem-solving, resulting in well-rounded graduates.

5.8. Long-Term Workforce Stability

By ensuring a better match between candidates and job roles, it decreases turnover and contributes to a more stable and motivated workforce.

6. Methodology of the Research and Result

The research adopts a systematic, data-driven strategy to improve the recruitment process through machine learning models. The methodology includes the following essential phases:

6.1. Data Collection

Data is collected from university departments and students which encompasses:

- Academic records
- Work experience
- Technical skills
- Extracurricular achievements
- Additionally, data from companies regarding job criteria and hiring trends is gathered.

6.2. Data Pre-processing and Transformation

The collected data undergoes cleaning and standardization. A binary transformation (0 or 1) is applied according to company-specific hiring criteria. Feature engineering is conducted to extract relevant attributes for the machine learning models.

6.3. Feature Selection

Important features that impact candidate selection are identified using statistical and company requirement. These features include academic performance, technical skills, project experience, and competencies relevant to the industry.

6.4. Data Generation for Model Training

Various recruitment scenarios are simulated based on the selected features. The dataset is divided into training and testing sets to ensure thorough model evaluation.

6.5. Machine Learning Model Implementation

Distinct machine learning algorithms are employed to predict candidate selection some of them are:

- Decision Tree
- Random Forest
- Boosting Algorithms (e.g., XGBoost)
- SVM
- Linear Regression

6.6. Model Validation and Performance Evaluation

The trained models are evaluated using a separate dataset. Evaluating model performance in machine learning is essential for ensuring the reliability and applicability of algorithms. Different evaluation metrics serve as benchmarks to quantify a model's effectiveness, each offering unique insights. Some of the most commonly used metrics include accuracy, precision, recall (sensitivity), and the F1 score [33].

1. Accuracy: it will shows the ratio of correctly predicted instances to the total instances in the dataset.

$$\text{Accuracy} = \frac{\text{True Positives} + \text{True Negatives}}{\text{Total Instances}}$$

2. Precision: it will show the ratio of true positive predictions to the total predicted positives. It measures the accuracy of positive predictions.

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

3. Recall (Sensitivity): it will show the ratio of true positive predictions to the total actual positives. It indicated that how well the model identifies positive instances.

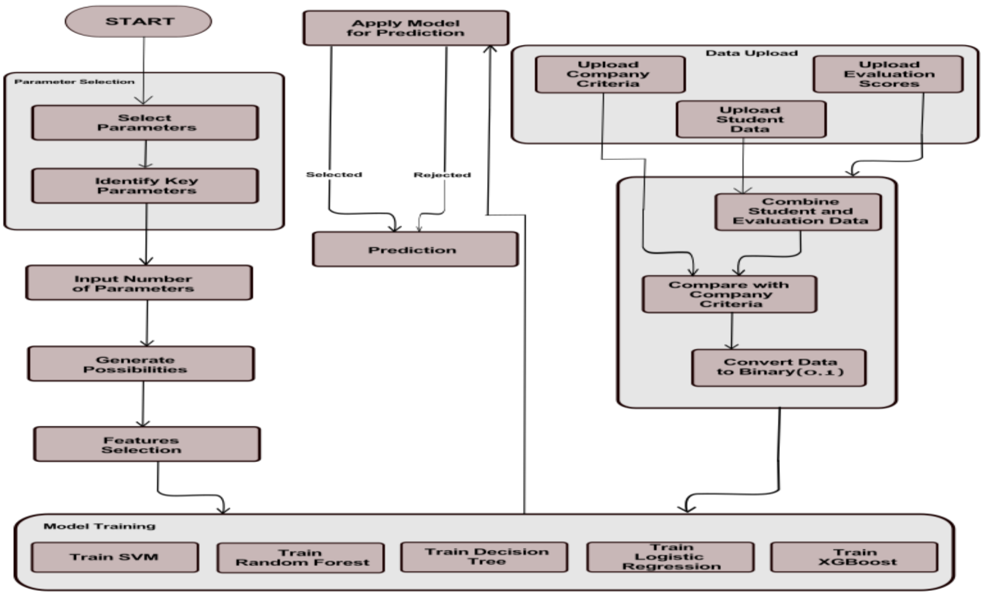
$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

4. F1 Score: the harmonic mean of precision and recall. It balances the two metrics, making it useful when you need a single measure of model performance.

$$\text{F1 score} = 2 * \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}$$

We can conclude with:

a) Proposed Methodology



b) Result

PLACEME-INTO Home Company Data Upload Score Upload Logout

10 entries per page Search:

id	Name	SSC	HSC	HEducation	HE(%)	Exp	Certificates	Hackathon	Academic	Specialization	Aptitude	Technical	Verbal	HR	Result
0	Person 1	60	60	MCA	65	NO	JAVA	Python	Android	Python	50	45	50	50	Rejected
1	Person 2	60	60	MCA	70	YES	Python	MYSQL	Android	Python	70	65	65	70	Selected
2	Person 3	60	60	MCA	60	NO	Data Science	Python	Python	Data Science	65	65	65	60	Rejected
3	Person 4	60	60	MCA	60	YES	Python	NO	Python	NO	55	55	65	50	Rejected
4	Person 5	60	75	MCA	70	NO	Python	NO	Python	NO	55	65	55	60	Rejected
5	Person 6	60	75	MCA	70	YES	Java	Web Services	Python	MYSQL	55	65	65	60	Rejected
6	Person 7	60	75	MCA	60	NO	Data Science	Python,	Python	Data Science	65	65	65	60	Rejected
7	Person 8	60	75	MCA	60	YES	Python	NO	Android	Python	55	55	65	50	Selected
8	Person 9	75	60	MCA	70	NO	Python	NO	Android	NO	55	65	55	60	Rejected
9	Person 10	75	60	MCA	70	YES	Java	Web Services	Android	MYSQL	55	65	65	60	Rejected
id	Name	SSC	HSC	HEducation	HE(%)	Exp	Certificates	Hackathon	Academic	Specialization	Aptitude	Technical	Verbal	HR	Result

Showing 1 to 10 of 100 entries

« ‹ 1 2 3 4 5 ... 10 › »

c) Comparison: Existing vs. Proposed Methodology

Aspect	Existing Methodology	Proposed Methodology
Candidate Evaluation	Generic aptitude and technical tests	Tailored, parameter-driven assessments
Focus Area	Primarily technical knowledge	Holistic, including soft skills and culture fit
Bias	Prone to subjective biases	Objective, data-driven decisions
Industry Alignment	Often misaligned with industry needs	Highly aligned with company expectations
Scalability	Limited adaptability for diverse roles	Easily customizable for multiple industries
Time Efficiency	Lengthy, with repetitive tests	Streamlined screening with predefined parameters
Inclusivity	Favours students from urban/well-resourced colleges	Diversifies talent pool, focusing on potential
Training Costs	High costs due to misaligned skills	Reduced training costs with better skill matching
Student Preparation	Unclear expectations for students	Clear parameters for effective preparation
Retention & Performance	High attrition due to mismatched roles	Better job-role fit leads to higher retention

7. Achievements with respect to Objectives

The research effectively achieves its goals by implementing a data-driven, AI-powered recruitment system that boosts hiring efficiency, minimizes biases, and enhances student employability. Below are the key accomplishments related to each research objective:

Objective	Achievement
Develop an AI-Driven Hiring Model to Improve Candidate Selection	• Utilized Decision Tree, Random Forest, and Boosting algorithms to accurately predict student placement outcomes with 99% precision. • Established a binary transformation model that standardizes candidate evaluations based on specific company parameters.
Enhance the Efficiency of the Recruitment Process Achievement	• Shortened the hiring timeline through automated the processes of resume screening, shortlisting, and matching, significantly reducing manual workload. • Created an adaptive assessment engine that evaluates candidates according to the changing needs of the industry
Improve Candidate-Job Fit through Data-Driven Decision Making Achievement:	• Developed a role-specific dynamic scoring model that ensures candidates align with job requirements beyond generic test scores.
Reduce Biases and Ensure Fair Hiring Practices	• Implemented an ethical hiring framework that reduces subjective biases and encourages merit-based selection. • Provided structured training and support to underprivileged students to enhance their employability
Strengthen Academia-Industry Collaboration	• Created a dynamic repository of industry-backed parameters, enabling companies to update hiring criteria in real time. • Fostered partnerships between universities and companies for curriculum updates, internships, and workshops.

8. Conclusion

The study does an efficient job of addressing the limitations of conventional campus placement by presenting a data-backed, AI-based hiring mechanism that supports an equitable, effective, and holistic method of candidate selection. It stresses the importance of integrating academic merit, technical competence, interpersonal skills, and current industry perceptions in enhancing employability and enhancing the job-role match.

Using machine learning algorithms such as Decision Tree, Random Forest, and Boosting, the system has a remarkable accuracy of 99% in prediction, significantly improving the efficacy of the recruitment process. A role-oriented dynamic scoring model prevents mismatching and ensures better retention rates by enabling companies to tailor candidate selection as per shifting industry demands.

In addition, the research promotes ethical recruitment through the minimization of prejudices and provision of equal opportunities for people from diverse backgrounds. It supports robust partnership between industry and academia, which helps educational institutions link their courses to industry needs, thereby better preparing students and enhancing long-term labour stability.

The model also maximizes resource utilization by reducing recruitment time and training costs, thereby making the hiring process more efficient and scalable. Organizations benefit from employing ready-to-work candidates, while students reap the reward of well-defined career progress with systematic training and assessment.

9. Publications

Type	Authors	Title	Publication Details	DOI/ISSN
Journal	Monica Gupta, Sohil D Pandya	A Comparative Study on Supervised Machine Learning Algorithm	International Journal for Research in Applied Science and Engineering Technology, 10, 1023-1028 (2022)	https://doi.org/10.22214/ijraset.2022.39980

Journal	Monica Gupta, Sohil D Pandya	Machine Learning-Based Predictive Modeling for Recruitment and Selection in Campus Placement Processes	Journal of Electrical Systems, 20, 5233-5239 (2024)	1112-5209
Journal	Monica Gupta, Sohil D Pandya	Conceptualizing Decision-Making Processes for Campus Placements through Machine Learning	Advances in Nonlinear Variational Inequalities ISSN: 1092-910X Vol 28No. 4s(2025)	https://doi.org/10.52783/anvi.v28.4492
Conference	Monica Gupta, Sohil D Pandya	Recruitment and Selection Processes in Campus Placements with Machine Learning	Emerging Trends in Expert Applications and Security (ICE-TEAS 2024), Lecture Notes in Networks and Systems, Vol 1030, Springer, Singapore (2024)	https://doi.org/10.1007/978-981-97-3745-1_7

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