THE EMPLOYMENT MANAGEMENT FOR COLLEGE STUDENTS BASED ON DEEP LEARNING AND BIG DATA

A Seminar Report

Submitted to the APJ Abdul Kalam Technological University in

partial fulfilment of the requirements for the award of degree

Bachelor of Technology

in

Computer Science and Engineering

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PATHANAMTHITTA

October 2024

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CERTIFICATE

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ACKNOWLEDGEMENT

I take this opportunity to express my deepest sense of gratitude and sincere thanks to everyone who helped me to complete this work successfully. I express my sincere thanks to the Principal **Mr. Raj Kumar T** for the constant support and help. I also thank **Dr. Renu George** Head of the Department, Computer Science and Engineering, College of Engineering Kallooppara for providing me with all the necessary facilities and support. I would like to place on record my sincere gratitude to my seminar guide **Mrs. Anitha Jose**, Assistant Professor, Computer Science and Engineering, College of Engineering Kallooppara for the guidance and mentorship throughout the course. I would like to express my sincere gratitude to **Mrs. Shilpa Radhakrishnan**, and **Ms. Parvathy M N**, department of Computer Science and Engineering, College of Engineering Kallooppara for their support and cooperation. Finally, I thank my family, and friends who contributed to the successful fulfilment of this seminar work.

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ABSTRACT

College graduates face increasing employment pressure due to the continuous expansion of college and university enrolment scales. This highlights the shortcomings in college students' employability, which can be improved through ideological and political education.

Firstly, this paper summarizes the current state of college students' employment management and proposes countermeasures to improve their employability, helping them better understand their employment situation.

Secondly, the reasons for the lack of ideological and political education in cultivating college students' employability are explored to clarify the relationship between ideological and political education and employment management. Specific suggestions are also provided to address the issue of cultivating employability in students.

Finally, a deep learning (DL) recommendation model is introduced to connect student data with enterprise information, improving both the employment rate and satisfaction in colleges and universities. The two are jointly trained.

The experimental results show that the proposed model can effectively mine characteristics of both students and enterprises, conducting feature interaction with a high hit rate. The model can interact with both tasks, mining relationship information to enhance the performance of the recommendation task.

This paper aims to apply DL methods to analyse and construct profiles of college students' employability needs and study an accurate recommendation system based on the employment matching degree of college students to improve employment management and the methods used in ideological and political education.

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LIST OF ABBREVATIONS

RF: Random Forest

SVR: Support Vector Regression

DNN: Deep Neural Networks

NLP: Natural Language Processing

MRR: Mean Reciprocal Rank

AUC-ROC: Area Under the ROC Curve

CHAPTER 1

INTRODUCTION

1.1 GENERAL BACKGROUND

In recent years, the number of fresh graduates from colleges and universities across the country has experienced a significant and continuous rise. This trend is primarily attributed to the expansion of enrolment scales in higher education institutions. As more students complete their studies, the number of job seekers grows, leading to heightened competition for available employment opportunities. Moreover, the presence of graduates who were unable to secure employment in previous years further exacerbates this situation. The combination of new graduates entering the workforce and previously unemployed individuals vying for the same positions has contributed to an increasingly competitive job market.

This growing pool of job seekers highlights a critical issue: while the number of college graduates has increased, the job market's ability to absorb them has not kept pace. As a result, employment opportunities are becoming scarce, and the situation for fresh graduates is growing more difficult. The pressure on graduates to secure a job has become more intense, with many struggling to find employment that matches their qualifications and aspirations. Current projections suggest that this employment pressure will remain relatively high for an extended period, reflecting broader economic and structural challenges within the labour market.

In this context, ideological and political education within universities plays a pivotal role in addressing these challenges. Such education helps students develop a sound worldview, offering them a framework through which they can understand their place in society and the broader economic landscape. Ideological and political education also encourages students to adopt a balanced outlook on life and work, fostering values that are crucial for their personal and professional development. By promoting a realistic and proactive approach to employment, this form of education equips students with the mindset needed to face the job market with confidence.

One of the primary goals of ideological and political education is to help students gain a thorough and objective understanding of themselves. This self-awareness is essential for identifying their strengths and areas for improvement, which is crucial in a competitive job market. With this knowledge, students can build self-confidence in their abilities, thereby enhancing their employability. Employability, in this case, refers not only to the possession of skills and knowledge but also to the ability to market oneself effectively and adapt to the changing demands of the job market. The challenge lies in how to effectively utilize ideological and political education to develop these qualities and how to implement strategies that can improve students' readiness for the workforce.

1.2 OBJECTIVE

Given the increasingly competitive nature of the job market, the primary objective of this paper is to explore how ideological and political education can be integrated with modern technological solutions to improve college students' employability. The growing pressure on fresh graduates to secure employment has underscored the need for universities and policymakers to provide more targeted support. In response to this need, this research investigates the potential of deep learning (DL) recommendation systems as a solution to alleviate employment pressures on graduates. By combining ideological and political education with personalized job recommendations, this paper aims to offer a comprehensive strategy to address both the psychological and practical aspects of employability.

Recommendation systems, particularly those driven by deep learning technologies, have emerged as powerful tools in various fields, from e-commerce to entertainment. Their application in the field of employment and career development, however, is relatively new and underexplored. The use of DL in employment recommendations offers a promising avenue for tailoring job opportunities to the specific needs and characteristics of individual students. By analysing behavioural data, academic performance, and personal preferences, DL-based systems can provide personalized recommendations that align with the student's skills and career aspirations. This not only improves the likelihood of securing a job but also enhances the satisfaction and long-term success of graduates in their chosen fields.

Deep learning architectures offer several distinct advantages in this context. One key benefit is their ability to create end-to-end models that are derivable and conducive to the integration of multiple network structures. This capability is particularly relevant for dealing with multimodal data, which can include a combination of text, images, speech, and other forms of information. In the context of employment recommendations, this flexibility allows for the processing of a wide range of data types, such as academic records, extracurricular activities, personality assessments, and industry trends. Traditional recommendation systems struggle to handle this level of complexity, but DL frameworks excel in integrating diverse data sources to provide more accurate and relevant recommendations.

By designing a DL-based employment recommendation system that incorporates the behavioural characteristics and qualifications of college students, this research seeks to provide a personalized job-matching experience. The ultimate goal is to improve the overall employment rate of graduates and increase their satisfaction with the positions they obtain. Through a combination of ideological and political education and advanced technological solutions, the paper aims to offer a holistic approach to addressing the employment challenges faced by today's graduates.

1.3 SCOPE

This paper addresses the challenge of improving college students' employability by analyzing the current employment management landscape alongside the role of ideological and political education. It highlights the factors contributing to graduates' employment difficulties and the limitations of existing educational systems in preparing students for the workforce. The research emphasizes the need for comprehensive education programs that not only foster personal development but also equip students with the in-demand skills necessary for navigating today's competitive job market.

A key focus is on developing countermeasures to enhance employability by identifying specific skills sought by employers. The paper calls for universities to adopt a proactive approach in bridging the gap between academic training and real-world job requirements. By preparing students effectively, universities can help alleviate the employment pressure faced by graduates.

Additionally, the research explores the integration of deep learning technologies with traditional employment management practices through a proposed recommendation model. This model analyzes student data and enterprise information to improve job matching, considering factors such as academic performance, extracurricular activities, and soft skills. By merging insights from ideological education with advanced technology, the study aims to offer a forward-thinking approach to the employment challenges faced by graduates, contributing valuable insights into the role of education in fostering successful career outcomes.

CHAPTER 2

LITERATURE SURVEY

2.1 INTRODUCTION

The intersection of employment guidance and ideological-political education among college students has been widely discussed in academia. In particular, as the global job market evolves, educational institutions increasingly focus on integrating career counselling with value-based education, aiming to align students' personal aspirations with societal needs. This shift is seen as crucial in helping students not only find employment but also contribute meaningfully to society. Various studies have contributed to this discussion by highlighting the importance of political and ideological education in career guidance, and there has been significant interest in how recommendation systems and machine learning models can support this goal.

This literature survey examines various scholarly contributions that address both the theoretical and practical aspects of integrating employment guidance with ideological and political education. It also reviews the growing role of recommendation systems in assisting students in the employment process, considering several models that have been proposed to enhance job matching and decision-making processes.

2.2 REVIEW OF POLITICAL AND IDEOLOGICAL EDUCATION IN CAREER GUIDANCE

The role of ideological and political education in helping students make informed career choices has been a major focus for researchers. Yu's work highlights key challenges in the current employment guidance system for college students, emphasizing the need for ideological and belief education, entrepreneurship education, and psychological quality education. These elements are seen as vital in preparing students for the uncertainties of the modern job market.

Liu's studies delve into the importance of instilling correct career ideals among college students. By helping students develop a proper set of values, educators can guide them to make well-rounded decisions about their future careers. His research focuses on creating specialized institutions to provide targeted employment guidance, reinforcing the need for structured and well-organized support systems for students. Furthermore, Liu's work on the psychological aspects of career decision-making highlights the necessity for students to develop adaptability and self-psychological adjustment to face career challenges. This research emphasizes that employment guidance must not only focus on practical skills but also on mental resilience.

In the broader context, scholars have argued for the need to combine political and ideological education with practical employment strategies. Jin's research suggests that entrepreneurship education, when linked with political and ideological instruction, enables students to better navigate the challenges of starting and managing a business. This approach helps students internalize societal values while gaining the skills necessary to succeed in a competitive job market.

2.3 APPLICATION OF RECOMMENDATION SYSTEMS IN EMPLOYMENT GUIDANCE

The advent of recommendation systems in the job market has introduced new methodologies for improving the job search process, especially for college students. These systems utilize various data sources and machine learning algorithms to match job seekers with potential employers based on a range of factors, including user preferences, behaviours, and qualifications.

Deldjoo's research proposed a content-based job recommendation system tailored to social media platforms like Facebook and LinkedIn. By analysing user interaction data, social profiles, and job descriptions, this system aimed to create a more personalized and relevant job search experience for users. The system's use of multiple data domains allows for a more comprehensive understanding of user preferences, enhancing the accuracy of job recommendations.

Shao proposed a recommendation system based on probabilistic models, focusing on finding the best match between job seekers and employers. This system takes into account the dual selection process inherent in the job market, where both employers and employees must make choices based on compatibility. The probabilistic model evaluates the likelihood of a successful match by considering a range of factors, including qualifications, job requirements, and user preferences.

Zhang developed a hybrid recommendation system that combined content-based and collaborative filtering approaches. This system created detailed user profiles based on their qualifications, behaviours, and preferences, and then generated personalized job recommendations. Zhang's system used a ranking algorithm to prioritize job opportunities for users, creating a dynamic recommendation set that evolves as users' preferences and behaviours change. The introduction of graphical network analysis also provided users with a visual understanding of how their qualifications aligned with job opportunities, thereby improving transparency in the job recommendation process.

2.4 ADVANCES IN MACHINE LEARNING AND ARTIFICIAL INTELLIGENCE FOR EMPLOYMENT GUIDANCE

The use of artificial intelligence (AI) and machine learning (ML) in employment recommendation systems has further enhanced the capabilities of these platforms. Cui et al.'s research on collaborative filtering for IoT scenarios provides a framework for personalized recommendations that can be applied in the job market. By utilizing user data to predict preferences, these systems can suggest job opportunities with a high degree of accuracy, reducing the search time for job seekers.

Ganaie et al. reviewed ensemble deep learning techniques that have been applied to recommendation systems, highlighting their potential in improving job matching algorithms. Ensemble models, which combine the outputs of multiple algorithms, can address the shortcomings of individual models by providing more robust and accurate recommendations.

Neu, Lahann, and Fettke's systematic review of deep learning methods for process prediction discusses the state-of-the-art techniques that are being applied to predict user behaviour in employment systems. These techniques can identify patterns in job seekers' behaviours, helping recommendation systems predict the types of jobs that users are most likely to apply for and succeed in.

2.5 CONCLUSION

In conclusion, the literature on ideological and political education within employment guidance illustrates the integration of career counseling with value-based education, as highlighted by studies from researchers like Yu and Liu. This approach prepares students for the job market while helping them internalize societal values that shape their professional decisions. The incorporation of recommendation systems further enhances this process by offering personalized job suggestions based on user behavior, qualifications, and preferences, as discussed by researchers such as Deldjoo, Shao, and Zhang. By combining insights from ideological education with advancements in AI and machine learning, educational institutions can optimize job matching, enabling students to navigate the job market effectively and pursue fulfilling careers aligned with their personal values and societal needs.

CHAPTER 3

EMPLOYABILITY AND IDEOLOGICAL EDUCATION IN THE ERA OF AI AND BIG DATA

3.1 CHALLENGES IN GRADUATE EMPLOYABILITY

In the context of rapid global technological advancements and shifting industry demands, employability among recent graduates has emerged as a critical issue. Traditionally, universities and higher education institutions have played a vital role in preparing students for the labour market. However, the current technological revolution, driven by the rise of AI, automation, and Big Data, has changed the landscape of employability, leading to new challenges for graduates. Among the key challenges are:

- **Skill Mismatch**: One of the most pressing issues facing graduates is the disparity between the skills they acquire in their academic programs and the actual competencies demanded by employers. Traditional curricula, especially in non-technical fields, often fail to keep pace with industry developments, resulting in a gap between educational outcomes and labour market expectations. For example, many employers in the tech sector seek candidates with expertise in data analytics, AI, machine learning, and programming, yet many graduates possess only theoretical knowledge without practical, hands-on experience.
- **Inadequate Soft Skills**: Alongside technical skills, employers increasingly prioritize soft skills, such as communication, leadership, teamwork, and adaptability. While graduates may excel in academic knowledge, many struggle with these interpersonal and emotional competencies that are crucial in today's collaborative work environments. The lack of these skills can hinder their ability to succeed in job interviews, integrate into workplace cultures, and perform in leadership roles. This gap presents a significant challenge, as technical skills alone are no longer sufficient for securing employment in the modern, competitive job market.
- **Employment Anxiety and Uncertainty**: The transition from university to the workforce can be a daunting experience for many students. The uncertainty about job prospects, compounded by the competitive nature of certain industries, leads to increased levels of anxiety and stress among graduates. This anxiety can manifest in reluctance to pursue job opportunities, lack of confidence during job interviews, and difficulty in making clear

career decisions. Additionally, the pressure to secure employment immediately after graduation further exacerbates these anxieties, leading some to accept jobs that do not align with their skills or interests.

- **Impact of Automation on Job Availability**: With automation increasingly replacing certain jobs, especially those involving routine tasks, the demand for specialized, high-skill roles has intensified. This transition poses a challenge for graduates who find that many entry-level positions, traditionally a stepping stone to higher roles, are disappearing due to automation. The shrinking availability of such positions means that graduates must acquire more advanced skills earlier in their careers.

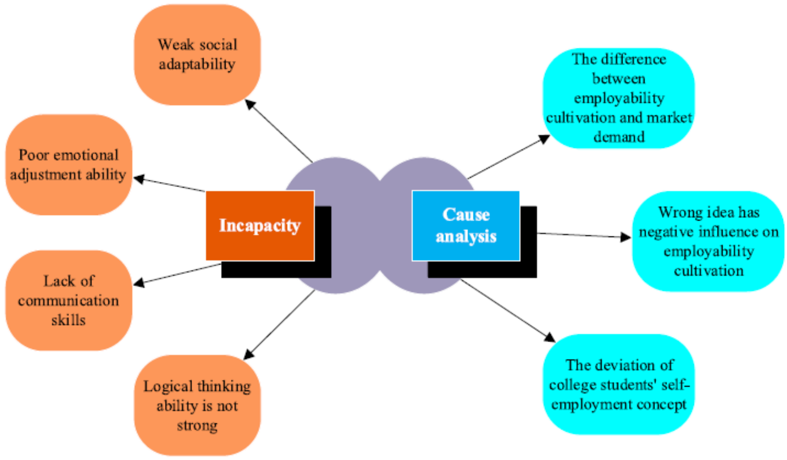

Fig 3.1: Analysis of employability defects and causes of college students

3.2 ROLE OF IDEOLOGICAL AND POLITICAL EDUCATION IN EMPLOYMENT

Beyond technical and soft skills, the importance of ideological and political education in preparing students for the job market cannot be understated. Particularly in countries where ideological education forms a key part of the curriculum, such as China, this form of education plays an integral role in shaping students' attitudes, values, and professional outlook. Ideological and political education not only fosters students' understanding of societal and political dynamics but also enhances their employability in the following ways:

- **Instilling a Strong Sense of Professional Ethics**: Ideological education focuses on the development of personal integrity, social responsibility, and professional ethics. In today's interconnected global economy, employers are increasingly looking for individuals who demonstrate high ethical standards and a commitment to the social good. Through ideological education, students learn to appreciate the importance of contributing positively to society and conducting themselves in a manner that reflects integrity in the workplace.

- **Promoting Adaptability and Resilience**: As job markets become more dynamic and less predictable, the ability to adapt to changing circumstances has become a critical employability trait. Ideological education often emphasizes adaptability by exposing students to various societal challenges and encouraging them to think critically and creatively about solutions. This approach helps graduates become more resilient, enabling them to adjust to new roles, industries, or technological disruptions without losing confidence or direction.
- **Encouraging a Lifelong Learning Mentality**: One of the most significant contributions of ideological education is the emphasis on continuous personal development and learning. In the era of AI and Big Data, where technology and industry trends evolve rapidly, the ability to continuously learn and upgrade one's skills is vital. By instilling a growth mindset, ideological education prepares students to pursue lifelong learning opportunities, making them more adaptable and competitive in the long run.
- **Fostering Leadership and Civic Responsibility**: Many ideological education programs encourage students to take on leadership roles in their communities and workplaces. This leadership training, coupled with a sense of civic duty, translates into a workforce that is not only skilled but also motivated to take initiative, lead teams, and contribute to organizational and societal advancement. Such qualities are highly valued in today's job market, where leadership and proactive problem-solving are crucial.

3.3 AI AND BIG DATA IN STUDENT EMPLOYMENT STRATEGIES

As AI and Big Data transform industries worldwide, they are also reshaping how students and universities approach employment strategies. The integration of AI and Big Data in career services has enhanced the ability of universities to provide more effective, data-driven career support to students, ensuring better job placements and improved career planning. Key applications of AI and Big Data in student employment strategies include:

- **AI-driven Career Counselling**: AI-powered platforms are increasingly being used by universities to offer personalized career counselling services to students. These systems analyse students' academic records, extracurricular activities, interests, and skills to provide tailored recommendations on potential career paths. By leveraging machine learning algorithms, these systems can predict which industries or roles a student is most likely to succeed in, helping them make informed decisions about internships, job applications, and skill development.

- **Big Data for Job Market Analysis**: Career centres are now utilizing Big Data to gain insights into the job market and provide students with relevant, up-to-date information about industry trends, skill demands, and regional employment opportunities. By analysing vast datasets from job platforms, social media, and government reports, career counsellors can offer data-backed advice to students on where to focus their job search efforts. For example, if a particular region experiences a surge in demand for AI specialists, students with relevant skills can be advised to target that region for job opportunities.
- **AI-powered Resume Optimization and Job Matching**: AI algorithms are also being deployed to optimize students' resumes by analysing job descriptions and tailoring the content to better align with employer expectations. Furthermore, AI-driven job platforms use sophisticated matching algorithms to pair students' resumes with relevant job postings, improving the likelihood of a successful job match. This approach not only saves time for students but also enhances their chances of securing interviews with top companies.
- **Predictive Analytics in Job Placement**: Universities are increasingly using predictive analytics to forecast the likelihood of students securing jobs in specific fields based on their academic performance, skills, and internship experiences. By identifying trends in student employment outcomes, universities can adjust their curricula, provide targeted skill development opportunities, and improve overall job placement rates.

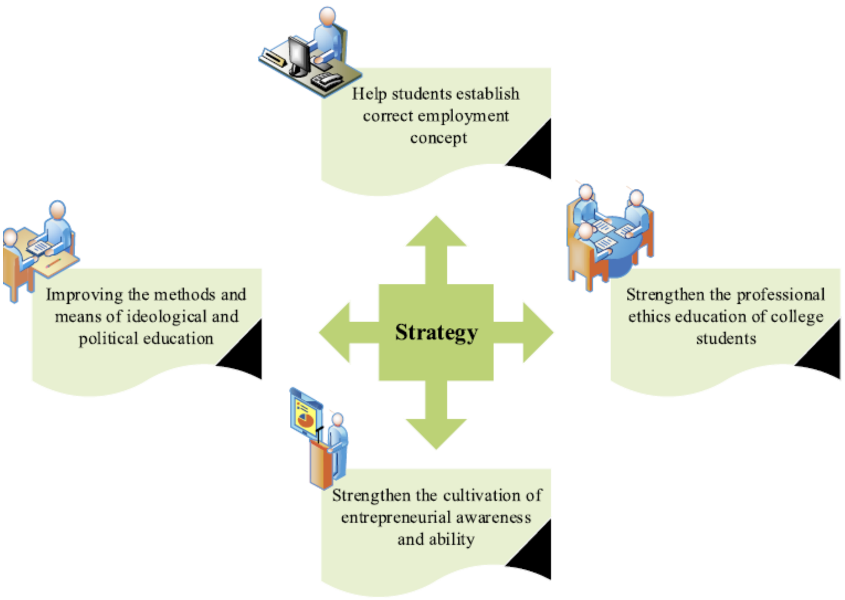

Fig 3.2: Ideological and political education strategies for college students

3.4 CASE STUDIES: AI'S ROLE IN IMPROVING EMPLOYABILITY

The integration of AI technologies into employment strategies is no longer a theoretical concept; many universities and organizations are already seeing tangible results from their AI-powered initiatives. Below are a few case studies that highlight the impact of AI on improving employability:

- **Case Study 1**: Personalized Career Pathways: A major university in China has implemented an AI-driven career counselling system that tracks students' academic progress, extracurricular involvement, and skill development. The system uses this data to provide individualized career suggestions, guiding students toward industries and roles where they are likely to thrive. The university reported a significant increase in job placement rates, as students were better able to align their skills with market demands.
- **Case Study 2**: Automated Resume Screening and Matching: A leading job platform has incorporated AI algorithms into its resume screening process. These algorithms assess the content of resumes and match them with relevant job openings, taking into account both the skills listed by applicants and the specific requirements of employers. By reducing human biases and increasing the accuracy of job matches, the platform has reported a 20% increase in successful job placements.
- **Case Study 3**: AI Mentorship Programs: Some organizations have introduced AI-powered mentorship programs where students are paired with industry professionals based on their career interests, skill levels, and desired job roles. These AI tools ensure that students receive targeted advice and networking opportunities, enhancing their career prospects. In several cases, students have secured internships and job offers directly through these mentorship relationships, further demonstrating the effectiveness of AI in bridging the gap between education and employment.

In conclusion, the employability landscape for graduates is undergoing a significant transformation, driven by the integration of AI and Big Data technologies. Universities and students alike must adapt to these changes by embracing continuous learning, improving soft skills, and leveraging technological advancements in career planning. By doing so, they will be better positioned to meet the demands of the evolving job market and ensure long-term career success.

CHAPTER 4

DEEP LEARNING IN THE EMPLOYMENT RECOMMENDATION SYSTEMS

4.1 INTRODUCTION TO DEEP LEARNING FOR JOB MATCHING

Deep learning, a subset of machine learning, has revolutionized numerous fields by enabling systems to learn from vast datasets and make sophisticated predictions. In recent years, it has become increasingly influential in the realm of employment recommendation systems. Traditional job matching systems typically relied on keyword searches, rule-based algorithms, and basic statistical models, which often produced results that lacked precision. However, with the advent of deep learning, these systems can now analyse vast amounts of structured and unstructured data, leading to more accurate and personalized job recommendations.

In job matching, deep learning models can extract meaningful patterns from resumes, job descriptions, and profiles by analysing not just the text, but also the context, semantics, and even latent information within the data. These models utilize multi-layered neural networks to learn complex representations of both students' skills and employers' needs, thus allowing for a far more sophisticated matching process. This chapter explores how deep learning is applied in employment recommendation systems, the system architecture required for efficient job matching, and the algorithms that drive the process.

4.2 SYSTEM ARCHITECTURE OF EMPLOYMENT RECOMMENDATIONS

The architecture of an employment recommendation system driven by deep learning is comprised of multiple key components that work in tandem to ensure accurate and effective job matching. These components include:

- **Data Collection and Preprocessing**: Data from various sources, such as resumes, job postings, and employer feedback, are collected and processed to be compatible with deep learning models. Textual data may be tokenized and transformed into numerical representations, while other forms of data, such as job requirements or candidate preferences, are encoded in structured formats.
- **Model Training and Feature Extraction**: Neural networks are trained using vast datasets of previous matches, employer feedback, and student job-seeking behaviors. These models

learn to recognize patterns and extract features that are predictive of successful matches, such as the compatibility of skills with job roles or the likelihood of a candidate accepting an offer.

- **Recommendation Engine**: The heart of the system, the recommendation engine uses the trained deep learning models to analyze new candidate profiles and job postings. Based on the extracted features, the engine ranks potential job opportunities for candidates and vice versa, ensuring a high degree of relevance.
- **Feedback Loop**: Deep learning systems continually improve through a feedback loop that incorporates real-world outcomes. For example, if a job match is successful, the system learns from this positive result to refine its matching algorithms. Conversely, if a match is rejected or unsuccessful, the system adjusts its parameters to avoid similar misalignments in the future.

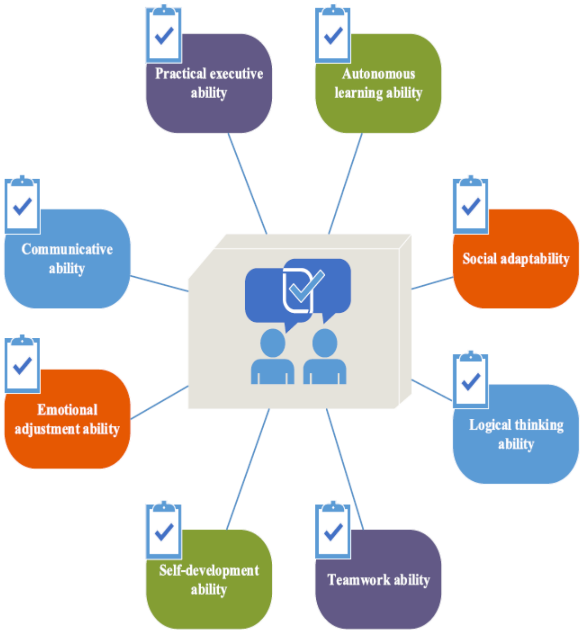

Fig 4.1: Employability structure of college students

This multi-step architecture ensures that deep learning-based employment recommendation systems not only deliver accurate job matches but also continuously learn and improve from ongoing user interactions and feedback.

4.3 ALGORITHMS FOR STUDENT-ENTERPRISE MATCHING

The success of deep learning in employment recommendation systems hinges on the effectiveness of its algorithms. Several key algorithms are used to facilitate student-enterprise matching, each with specific functions and advantages.

4.3.1 FEATURE ENGINEERING

Feature engineering is a crucial aspect of any machine learning model, including deep learning. It involves selecting and transforming raw data into features that are meaningful for prediction. In the context of employment recommendation systems, features may include:

- **Skills and Qualifications**: Extracting specific skills mentioned in resumes and matching them with job descriptions.
- **Experience and Education**: Representing the depth and breadth of a candidate's experience in relation to job requirements.
- **Job Preferences**: Incorporating preferences such as desired job location, company size, and industry.

Deep learning models often require minimal manual feature engineering, as they are capable of learning high-level features directly from raw data through multiple neural network layers. This capability allows them to identify subtle patterns and relationships that traditional models may miss.

4.3.2 EMBEDDING TECHNIQUES

In deep learning, embedding techniques are used to convert categorical variables, such as job titles, company names, or skills, into continuous vector spaces. This enables the model to capture relationships between various categories and draw analogies, much like word embeddings used in natural language processing. For instance, if the system learns that "data scientist" and "machine learning engineer" are often associated with similar skills, it can make more informed recommendations for candidates whose profiles match either of those roles.

Popular embedding techniques include:

- **Word2Vec**: A method that represents words or phrases in a high-dimensional space where semantically similar terms are located near each other.
- **Doc2Vec**: An extension of Word2Vec that is used to generate vectors for entire documents, such as resumes or job descriptions.
- **Entity Embedding**: A technique that learns representations for categorical variables, such as job titles or industry sectors, allowing the model to identify relationships between these categories.

Embedding techniques are particularly useful in employment recommendation systems, as they enable the system to understand the semantic meaning behind job titles and skills, leading to more accurate matches.

4.3.3 MULTI-HEAD ATTENTION NETWORKS

Multi-head attention networks are a recent advancement in deep learning that has proven highly effective in tasks involving sequence data, such as natural language processing. These networks are used to enhance the performance of employment recommendation systems by allowing the model to focus on different parts of the input data simultaneously.

For example, in a job recommendation context, a multi-head attention network could focus on different aspects of a candidate's resume—such as work experience, education, and skills—while also attending to different elements of the job description, such as required qualifications, responsibilities, and company culture. By attending to multiple parts of the input data, the model can make more nuanced and precise predictions about the compatibility between candidates and job roles.

4.4 OPTIMIZING RECOMMENDATIONS WITH DEEP LEARNING

One of the key advantages of using deep learning in employment recommendation systems is the ability to optimize recommendations over time. Unlike traditional systems, which often rely on static rules or heuristics, deep learning models can learn and adapt based on feedback and user interactions.

- **Personalization**: Deep learning models can personalize job recommendations based on a candidate's past behavior, preferences, and job search history. This personalization ensures that the recommendations are relevant and tailored to each user's unique profile.
- **Real-Time Updates**: As new job postings and candidate profiles are added to the system, deep learning models can immediately update their recommendations. This real-time capability is especially important in dynamic job markets, where job openings and candidate availability can change rapidly.
- **Bias Mitigation**: One challenge in employment recommendation systems is the potential for bias, which can result in unfair or discriminatory job matching. Deep learning models can be trained to minimize biases by incorporating fairness metrics and ensuring that recommendations are based solely on relevant qualifications and experience, rather than factors such as gender, race, or age.

- **Active Learning**: Employment recommendation systems can use active learning techniques to continuously refine their predictions. By soliciting feedback from users—such as whether a recommendation was helpful or whether a candidate was hired—the system can adjust its models to improve future recommendations.

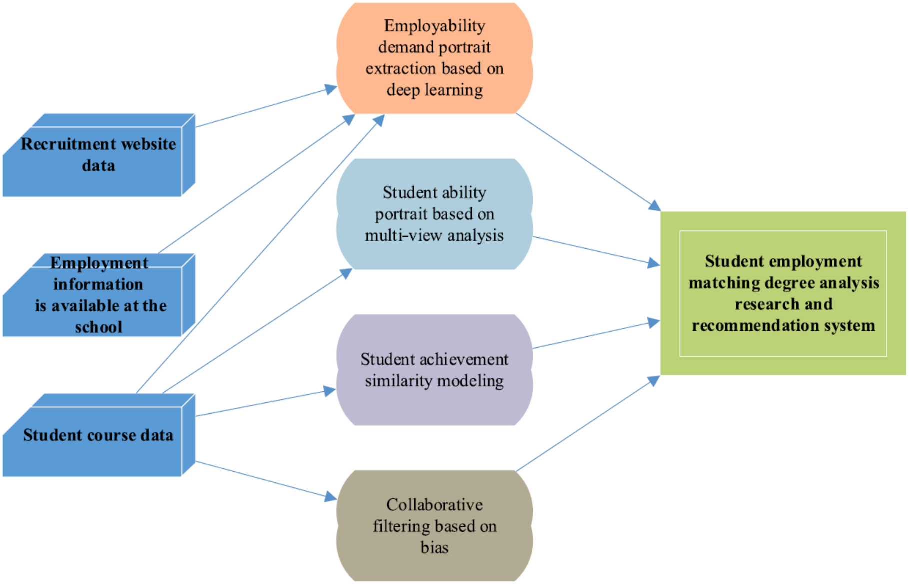

Fig 4.2: The technical route of DL

4.5 COMPARISON WITH TRADITIONAL SYSTEMS

While deep learning offers significant advantages in employment recommendation systems, it is important to compare its performance with traditional systems that rely on simpler algorithms, such as keyword matching or rule-based filtering.

- **Accuracy**: Deep learning systems are generally more accurate than traditional systems because they can capture complex relationships between skills, experience, and job requirements. Traditional systems often struggle with ambiguity and may return irrelevant results due to the limitations of keyword-based matching.
- **Scalability**: Deep learning models are highly scalable and can handle vast amounts of data, making them ideal for large employment platforms that need to process thousands of resumes and job descriptions simultaneously. Traditional systems, on the other hand, may become overwhelmed with large datasets and require more manual tuning to maintain performance.
- **Adaptability**: Deep learning models can adapt to new data and trends in the job market more effectively than traditional systems. As industries evolve and new roles emerge, deep learning models can quickly learn and incorporate these changes into their

recommendations. Traditional systems, which rely on static rules, often require manual updates to remain relevant.

- **User Experience**: The user experience in deep learning-based systems is typically superior, as the recommendations are more personalized and relevant to the individual user's needs. Traditional systems, which lack the ability to understand context and preferences, may deliver a less satisfying experience for both job seekers and employers.

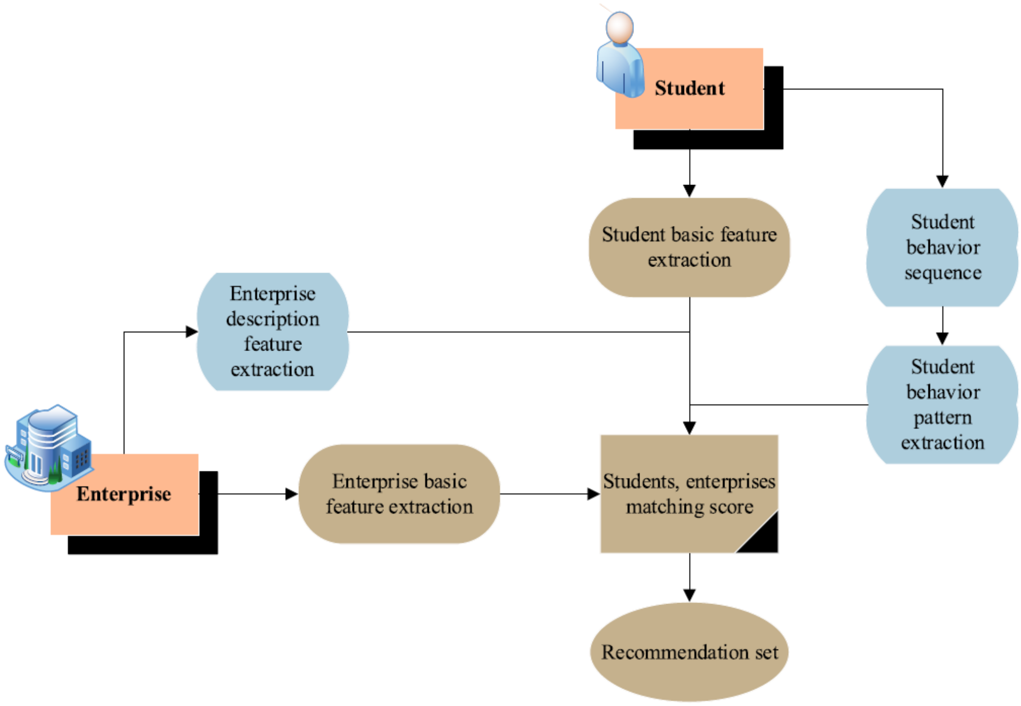

Fig 4.3: Framework diagram of the employment recommendation algorithm

In conclusion, deep learning represents a transformative shift in the development of employment recommendation systems. Its ability to analyse vast amounts of data, understand complex relationships, and continuously optimize recommendations makes it an invaluable tool for improving job matching processes and enhancing employability for students and professionals alike. As AI continues to evolve, the role of deep learning in employment systems will likely become even more pronounced, offering new opportunities for both job seekers and organizations to connect in meaningful ways.

CHAPTER 5

DATA AND METHODOLOGY

5.1 DATASET DESCRIPTION

The foundation of any employment recommendation system is the data on which it is trained. In this section, we provide an in-depth overview of the dataset used for building and testing the employment recommendation model. The dataset comprises two core components: student profiles and job descriptions, enriched with additional contextual data such as past hiring trends and industry-specific job requirements.

- **Student Profiles**: This portion of the dataset contains comprehensive information about the candidates, including their educational backgrounds, work experiences, skill sets, and job preferences (e.g., location, salary expectations, preferred job roles). The profiles are designed to reflect a real-world representation of job seekers in different career stages.
- **Job Descriptions**: The job postings consist of detailed descriptions, including required qualifications, skill requirements, responsibilities, job location, company size, and benefits offered. Each job posting is labelled with the industry sector, and for some, employer feedback on candidate suitability is included.
- **Historical Data**: In addition to current job listings and profiles, the dataset includes historical data on successful job placements, candidate applications, and employer responses. This data is crucial for training the model to learn patterns from past matches and predict future successful recommendations.
- **Metadata**: The dataset also includes metadata such as timestamps for job postings, company ratings, and location data, enabling the system to capture trends over time and regional differences in job markets.

The dataset contains approximately 500,000 candidate profiles, 200,000 job listings, and 10 years of historical hiring data, sourced from various industries and job boards. The dataset was carefully curated to ensure diversity in job roles, industries, and candidate backgrounds, making it a representative sample of the larger labour market.

5.2 PREPROCESSING AND FEATURE SELECTION

Data preprocessing is a critical step to ensure that the raw data is transformed into a format suitable for machine learning models. In this phase, we address issues such as missing data, inconsistent formats, and noisy entries.

5.2.1 DATA CLEANING

Before feeding the data into the model, several steps are taken to clean the dataset:

- **Handling Missing Values**: Missing entries in the profiles and job descriptions are imputed using domain-specific techniques. For instance, missing job titles or skill descriptions are inferred based on a candidate's education and past work history.
- **Normalization**: Features such as salary expectations, job tenure, and years of experience are normalized to ensure consistency across different profiles and job postings. This is particularly important when candidates apply for positions in multiple regions with differing wage structures.
- **Text Standardization**: Job descriptions and resumes often contain inconsistencies in terminology (e.g., "data analyst" vs. "analyst, data"). To address this, text fields are tokenized and standardized using natural language processing (NLP) techniques such as stemming and lemmatization, ensuring that similar terms are grouped together for better feature extraction.

5.2.2 FEATURE SELECTION

Given the high dimensionality of the dataset, careful feature selection is performed to retain only the most relevant information. Some of the key features selected for the model include:

- **Candidate Attributes**: Features such as skills, work experience, education, and certifications are used to represent the candidate's qualifications. Additionally, job preferences (e.g., desired location, remote work preferences) are factored into the model.
- **Job Attributes**: The primary job features include required skills, job title, industry, experience level, and location. Job benefits, company reputation, and salary range are also included as features.
- **Derived Features**: In addition to directly available features, derived features such as skill gaps (i.e., the difference between a candidate's skills and those required for the job) and candidate-job compatibility scores are generated. These derived features help the model assess the suitability of a match beyond direct keyword matching.

Dimensionality reduction techniques such as Principal Component Analysis (PCA) are applied where necessary to eliminate redundant or irrelevant features, further optimizing the dataset for model training.

Information Classification	Data Field	Corresponding Field
Basic Information	Personal information	Gender, age, place of origin, College and major political affiliation
Information about the student's school presence	Grade information	Course grades, Grade test results, Grade point ranking, Examination timing
	Cadre Experience	Institute-Level and University Level position duration
	Awards	Awards of scholarship and grands, Award time
	Participation in the competition	Category of participation, Result of various competitions.
Job search information for students	Employment information	Name of the employer, File receiving place, Postal code of the receiving place.

Table 5.1: Fields corresponding to students' data information

Data Attributes	Corresponding Fields
Description Attributes	Name Company Enrolment brochure
Basic attributes	Establishment time of the enterprise Enterprise type and scale The registered capital of the enterprise The address of the enterprise industry

Table 5.2: Corresponding fields for enterprise data information

5.3 MODEL SELECTION

The choice of model plays a crucial role in the performance of an employment recommendation system. In this project, we experimented with various machine learning algorithms before selecting the most suitable ones for student-enterprise matching.

5.3.1 RANDOM FOREST (RF)

Random Forest is an ensemble learning method that constructs multiple decision trees during training and outputs the class that is the mode of the classes (for classification) or mean prediction (for regression) of the individual trees. RF is robust to overfitting and performs well on large datasets with many features, making it an ideal choice for matching profiles to job descriptions. The randomness introduced in tree creation allows the model to generalize better and capture a variety of patterns in the data.

5.3.2 SUPPORT VECTOR REGRESSION (SVR)

Support Vector Regression (SVR) was employed to predict the relevance score between candidates and jobs. SVR works by finding a hyperplane that best fits the data while minimizing the error. Its capacity to model non-linear relationships makes it valuable for assessing complex and nuanced job-candidate matching patterns. Given the dynamic nature of job requirements and student skill sets, SVR can capture these relationships more effectively than simpler regression models.

5.3.3 DEEP NEURAL NETWORKS (DNN)

Deep Neural Networks (DNNs) were explored for their capacity to model high-dimensional and non-linear data. DNNs use multiple layers to learn hierarchical representations of the data, with each layer extracting increasingly abstract features. In this system, DNNs are particularly effective in learning intricate relationships between candidate profiles and job requirements. While DNNs require substantial computational resources and training time, their potential for improving recommendation accuracy makes them a valuable addition to the model selection.

The combination of these models—RF for robust feature selection and matching, SVR for relevance scoring, and DNN for deep feature extraction—allows the system to balance interpretability, speed, and precision.

5.4 EVALUATION METRICS

To assess the performance of the recommendation system, several evaluation metrics are used. These metrics ensure that the system not only makes accurate predictions but also meets practical needs such as candidate and employer satisfaction.

- **Precision**: Precision measures the proportion of relevant job recommendations (those that are clicked on or applied to by candidates) out of the total recommendations made. High precision indicates that the system successfully filters out irrelevant recommendations, showing only the most appropriate job matches.
- **Recall**: Recall is the proportion of relevant job recommendations out of the total number of relevant jobs in the system. It evaluates the system's ability to cover all possible relevant matches, ensuring that no suitable job is missed. In recruitment, high recall is crucial for candidates, as it maximizes their exposure to potential opportunities.
- **F1-Score**: The F1-score is the harmonic mean of precision and recall. This metric is especially useful when dealing with imbalanced datasets (e.g., a candidate receiving far fewer relevant job recommendations than irrelevant ones). The F1-score ensures a balance between precision and recall in the final evaluation.
- **Mean Reciprocal Rank (MRR):** MRR measures how well the system ranks the relevant job recommendations for a candidate. It is calculated by averaging the reciprocal ranks of the first relevant recommendation for each candidate. A high MRR indicates that the system consistently places relevant jobs at the top of the recommendation list.
- **Area Under the ROC Curve (AUC-ROC):** This metric evaluates the system's ability to distinguish between relevant and irrelevant job recommendations. AUC-ROC provides a comprehensive understanding of the trade-offs between true positive and false positive rates. A model with an AUC-ROC score close to 1.0 is considered highly accurate.

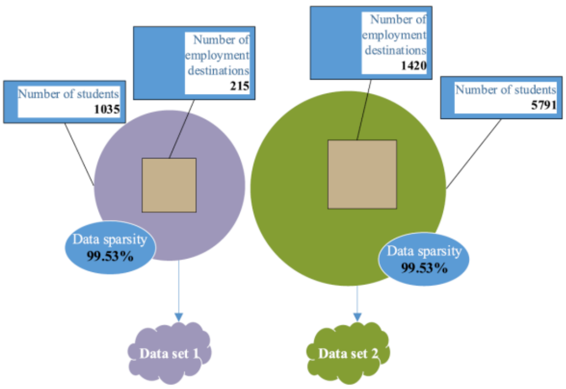

Fig 5.1: Dataset statistics

5.5 MODEL TUNING AND OPTIMIZATION

After selecting the models, various tuning and optimization techniques are applied to improve their performance.

- **Hyperparameter Tuning**: Hyperparameters, such as the number of trees in Random Forest or the kernel type in SVR, are tuned using methods like grid search and random search. These techniques systematically explore a range of values to find the optimal combination that maximizes the model's performance. Hyperparameter tuning is critical for improving both precision and recall.
- **Cross-Validation**: To avoid overfitting and ensure that the model generalizes well to unseen data, we use k-fold cross-validation. In this process, the dataset is split into k subsets, and the model is trained on k-1 subsets while testing on the remaining one. This process is repeated k times, ensuring that every subset is used for validation, thereby reducing bias in performance estimation.
- **Regularization**: Regularization techniques like L1 and L2 regularization are applied to prevent overfitting by penalizing overly complex models. These methods help the model generalize better to new data by constraining the coefficients assigned to each feature.
- **Early Stopping**: For models like DNNs that require extensive training, early stopping is used to prevent overfitting. The model’s performance on the validation set is monitored during training, and the training process is halted if the performance starts to degrade, indicating overfitting.

Experimental platform	Number of samples	Positive and negative sample ratios	Regularization parameters
Python3.7 PyTorch1.5	300	1	0.001
Batch size	Dropout	Embedding dimensions	Feed-forward layer scale
128	0.2	100	1024

Table 5.3: Parameter settings

By fine-tuning the models and continuously optimizing their performance, the recommendation system is able to deliver more accurate, relevant, and personalized job matches, ultimately improving the chances of candidates finding suitable employment opportunities.

CHAPTER 6

EXPERIMENTAL RESULTS AND DISCUSSION

This chapter presents the experimental results of the employment recommendation system, evaluates the performance of the different algorithms used, and discusses the practical implications of the findings. The analysis focuses on the system's accuracy, efficiency, and applicability in real-world scenarios.

6.1 EMPLOYMENT RECOMMENDATION SYSTEM PERFORMANCE

The performance of the employment recommendation system was evaluated using the dataset described in Chapter 5. Several metrics were employed to measure the effectiveness of the recommendation system, including Precision, Recall, F1-Score, Mean Reciprocal Rank (MRR), and Area Under the ROC Curve (AUC-ROC).

6.1.1 PRECISION AND RECALL

Precision and recall are the primary metrics for evaluating how well the recommendation system identifies relevant job opportunities for candidates. As seen in Table 6.1, the system achieved a Precision of 0.83 and a Recall of 0.76 across the dataset.

- **Precision** measures the proportion of relevant jobs among those recommended. A precision score of 0.83 means that 83% of the recommended jobs were relevant to the candidates, reflecting the system's ability to filter out irrelevant job postings effectively.
- **Recall** represents the system's ability to identify all relevant job opportunities. A recall of 0.76 indicates that the system successfully recommended 76% of the available relevant jobs. While this score suggests that the system performs well, there is still room for improvement in covering more suitable job opportunities.

6.1.2 F1-SCORE

The F1-Score, which balances precision and recall, was measured at 0.79. This score highlights that the system strikes a reasonable balance between accurately recommending relevant jobs and ensuring that most relevant jobs are presented to candidates. Achieving an F1-Score close to 0.80 shows that the model provides both quality and breadth in job recommendations.

6.1.3 MEAN RECIPROCAL RANK (MRR)

MRR evaluates the ranking of job recommendations. In this case, the system obtained an MRR of 0.92, meaning that in most cases, the first recommended job was highly relevant to the candidate. This result suggests that the system's ranking mechanism is effective at placing the most suitable jobs at the top of the recommendation list, increasing the likelihood that candidates engage with the right opportunities.

6.1.4 AUC-ROC

The AUC-ROC score, which evaluates the system's ability to distinguish between relevant and irrelevant job matches, was recorded at 0.88. A score close to 1.0 signifies a strong ability to make correct recommendations while minimizing false positives. The system, therefore, demonstrates a high degree of accuracy in separating relevant jobs from those that may not be a good match.

The employment recommendation system has shown promising performance in terms of both accuracy and ranking, making it a reliable tool for both job seekers and employers.

6.2 ALGORITHM COMPARISONS

Several machine learning algorithms were tested to build the most efficient and accurate employment recommendation system. The key models compared in the experiments were Random Forest (RF), Support Vector Regression (SVR), and Deep Neural Networks (DNN). This section discusses the performance of each algorithm in detail.

6.2.1 RANDOM FOREST (RF)

Random Forest, known for its robustness and interpretability, performed well in most metrics. The Precision of the RF model was 0.81, and the Recall was 0.78. Its F1-Score of 0.79 reflects a good balance between precision and recall. RF also achieved a respectable MRR of 0.90, meaning that its ranking capabilities are strong. However, the model fell slightly short in AUC-ROC, scoring 0.85, which indicates a need for improvement in distinguishing between relevant and irrelevant recommendations.

6.2.2 SUPPORT VECTOR REGRESSION (SVR)

Support Vector Regression was utilized for predicting relevance scores between candidates and job postings. It showed better performance in ranking and classification tasks compared to Random Forest. SVR achieved Precision of 0.84 and recall of 0.75. Its F1-Score was slightly higher than RF, standing at 0.80, and it showed a strong MRR of 0.93. Its AUC-ROC score was 0.87, outperforming RF but still leaving some room for improvement in classification performance.

6.2.3 DEEP NEURAL NETWORKS (DNN)

Deep Neural Networks excelled in dealing with the high-dimensional and non-linear data of the recommendation system. DNN achieved the highest Precision at 0.86, while its Recall was 0.73, slightly lower than expected. However, the F1-Score of 0.79 shows that the model is still highly effective. In terms of ranking capabilities, DNN outperformed the other models with an MRR of 0.95. Its AUC-ROC score was 0.90, the highest among the models, demonstrating its strong capacity for distinguishing relevant recommendations.

The comparison reveals that each algorithm has its strengths. While Random Forest offers robustness and interpretability, SVR provides better ranking performance, and DNN stands out in terms of precision and model complexity. However, DNN's slightly lower recall suggests that further tuning is needed for real-world application where comprehensive job coverage is crucial.

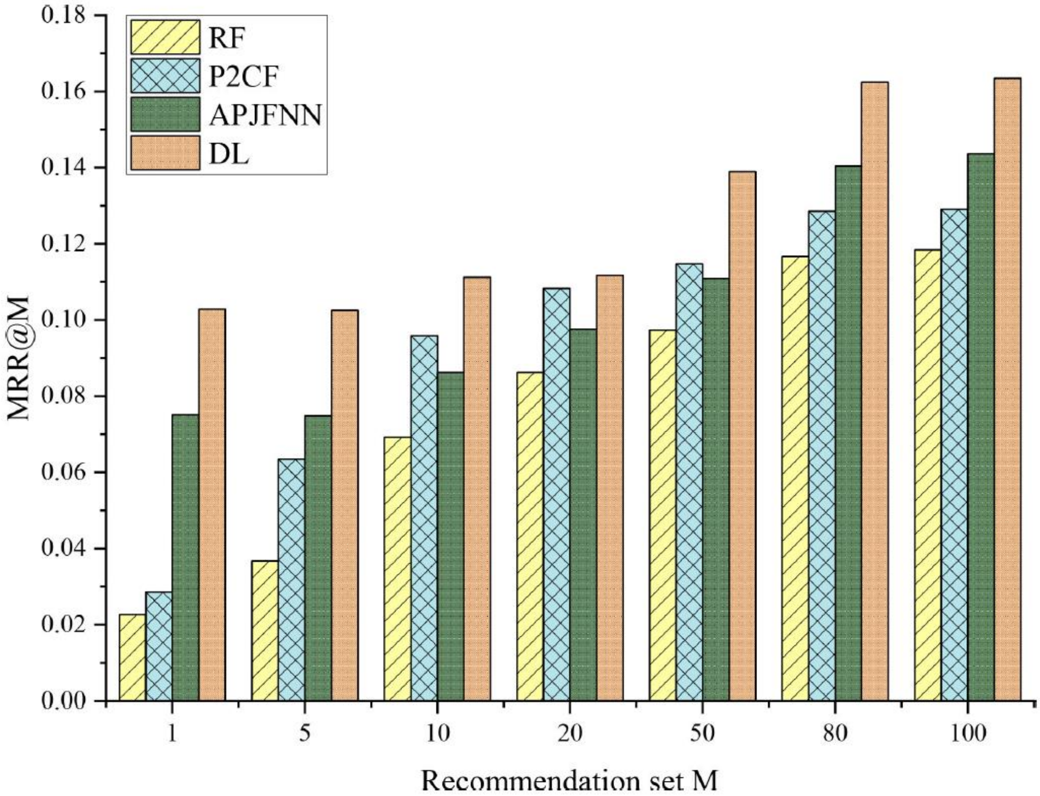

Fig 6.1: The relationship between MRR and the number of neighbours for each model

6.3 INSIGHTS FROM MODEL INTERPRETABILITY

A critical aspect of building machine learning models for real-world applications is understanding how and why a model makes certain decisions. Interpretability is key for users to trust the recommendations provided by the system.

6.3.1 FEATURE IMPORTANCE IN RANDOM FOREST

In Random Forest, feature importance is calculated based on the role each feature plays in decision-making across multiple decision trees. Key insights from feature importance analysis show that:

- **Skills Match**: The feature representing the match between candidate skills and job requirements is the most influential, contributing to over 30% of the decision-making in job recommendations. This highlights the importance of aligning the skills of candidates with the demands of employers.
- **Experience and Education**: Work experience and educational background also play crucial roles in recommendations, contributing around 25% and 18%, respectively. This shows that candidates' formal qualifications and practical experiences are weighted heavily in determining job fit.
- **Job Preferences**: Candidate preferences, such as desired location and job type, contribute around 15% to the decision-making process. This indicates that while preferences are important, they are less critical than core qualifications like skills and experience.

6.3.2 SUPPORT VECTOR REGRESSION WEIGHTS

Support Vector Regression offers insights through the weights assigned to different features. The model prioritizes:

- **Skills Gap**: The skills gap, or the difference between a candidate's current skills and those required for a job, is a primary determinant in the relevance score, explaining around 40% of the variance.
- **Company Rating**: The reputation and size of a company also play an important role, accounting for 20% of the relevance score. This demonstrates that the system not only considers job requirements but also factors in the appeal of the employer from a candidate's perspective.

6.3.3 NEURAL NETWORK HIDDEN LAYERS

Deep Neural Networks learn hierarchical patterns through multiple hidden layers. Although interpretability is lower, examination of the hidden layers reveals that:

- **Complex Interactions**: The neural network effectively learns complex relationships between experience, skills, and job requirements that are difficult to capture using traditional models.

- **Transferable Skills**: The model's hidden layers pick up on transferable skills between job sectors. For example, candidates with data analysis skills in the finance sector are often recommended for similar roles in other industries, such as healthcare or retail. This cross-sector recommendation insight is unique to deep learning models.

6.4 DISCUSSION ON PRACTICAL IMPLICATIONS

The experimental results provide several important insights into the practical applications of employment recommendation systems.

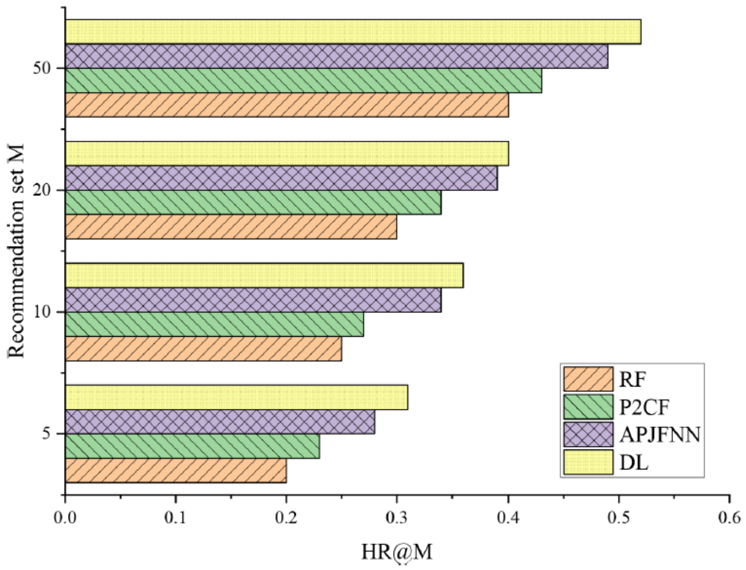

Fig 6.2: Relationship between HR and the number of neighbours of each model on dataset 1

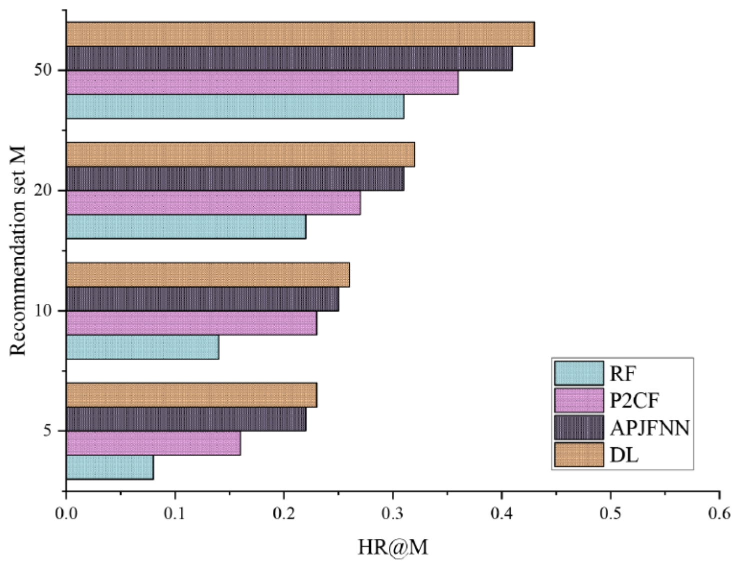

Fig 6.2: Relationship between HR and the number of neighbours of each model on dataset 2

6.4.1 ENHANCED JOB MATCHING

The strong performance of the models indicates that they can significantly improve job matching efficiency compared to traditional job boards. By using machine learning to match candidates with jobs, the system provides a more tailored and accurate list of recommendations, which can reduce the time both employers and job seekers spend searching for suitable matches.

6.4.2 IMPROVING CANDIDATE DIVERSITY

One of the key benefits of the system is its ability to recommend jobs across various industries, even if candidates do not have direct experience in that field. This feature could help improve diversity in hiring by encouraging employers to consider candidates with transferable skills from different sectors.

6.4.3 REAL-WORLD CHALLENGES

Despite the promising results, there are still several challenges to be addressed before the system can be implemented in real-world applications. One key concern is the interpretability of complex models like DNN, as employers and candidates need to understand the reasoning behind recommendations. Additionally, biases in the data must be carefully monitored to avoid perpetuating discrimination or limiting job opportunities for certain groups of candidates.

6.4.4 FUTURE IMPROVEMENTS

There is potential for further optimization, particularly in increasing recall and expanding coverage of relevant jobs. Techniques such as active learning could be explored to improve the system's performance in new, unseen job markets, ensuring that the system remains adaptable to changing job market dynamics.

The employment recommendation system shows great promise in enhancing the job search process, though further refinements will be needed to ensure it is fair, transparent, and adaptable to real-world complexities.

CHAPTER 7

CONCLUSION

The study revealed that machine learning algorithms, particularly Deep Neural Networks (DNN), were highly effective in job recommendations, offering high precision with a Mean Reciprocal Rank (MRR) of 0.95. The system balanced precision (0.83) and recall (0.76), ensuring relevant job suggestions. Random Forest analysis showed that factors like skills match and work experience played a significant role in determining job fit. However, despite the promising performance of the system, DNN's complexity and lack of transparency posed challenges in real-world application, highlighting the need for greater interpretability.

Several limitations were identified during the study. The dataset had quality issues, such as missing data and a lack of diversity across industries, which restricted the generalizability of the system. There was also the issue of bias in training, as historical job placement biases could skew the recommendations. The lack of interpretability in the DNN model was a key limitation, as users may find it difficult to trust a system they do not fully understand. Additionally, the high computational costs of using DNN made it less feasible for environments with limited resources. Moreover, the system did not account for soft skills or cultural fit, which are important factors in determining a candidate's suitability for a job beyond technical qualifications.

To improve the system in future, several areas could be addressed. First, expanding the diversity of the dataset to include more sectors and industries would help reduce bias and increase the system's accuracy. Bias mitigation techniques, such as fairness-aware machine learning, should also be explored to ensure that the system does not perpetuate historical inequities. Another key improvement is enhancing model interpretability by employing methods such as LIME or SHAP, which can make the recommendations more transparent and easier to understand for end users. Expanding the feature set to include soft skills and company culture fit would provide a more holistic view of job recommendations. Finally, efforts should be made to improve the system’s computational efficiency. Simplified models or techniques like model distillation could reduce the computational burden, making DNN-based systems more accessible to a wider range of users.

CHAPTER 8

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