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Natural Language Processing (NLP) in AI-Driven Recruitment Systems

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ABSTRACT

The focus of this study is the use of Natural Language Processing (NLP) to help improve AI-based recruitment systems. The goal is to train and tune NLP models to help speed up the screening, ranking, and matching of job candidates using resumes and job descriptions. To improve recruitment chatbots, advanced models like BERT and GPT are adopted to promote dynamic candidate interaction as well as initial interviews. The study also involves constructing an NLP-driven interview simulation tool based on Hiring Manager input, create which aids ensure better candidate suitability by emulating real interactions. The research then extends the semantic search algorithm to refine the selection of candidates from large HR databases. The study seeks to address the recruitment efficiency, candidate fit and engagement challenges by integrating these methods into a more effective and streamlined hiring process.

Keywords : Natural Language Processing (NLP), AI-Driven Recruitment, BERT, GPT, Recruitment Chatbots, Semantic Search Algorithms.

I. INTRODUCTION

However, Artificial Intelligence (AI) and Natural Language Processing (NLP) have changed the recruitment process dramatically in how they can tackle the challenges in an automated way. AI-driven systems aimed to enhance the speed, resources, and accuracy of recruitment technology and the recruitment process as a whole are now the norm. A subset of AI, NLP allows machines to understand human language and create human language which is essential to dissect resumes, identify job descriptions, [1-3] and even conduct initial job interviews through chatbots. This work analyzes how AI-driven recruitment systems that use NLP models such as BERT and GPT can improve decision-making as well as candidate interaction.

Algorithms that are NLP make you understand relationships and structures in the language. Humans need context, while machines require advanced algorithms that are language and conversation-specific. NLP is typically divided into two main areas:

Comprehension using Natural Language Understanding (NLU) and human-like responses using Natural Language Generation (NLG). As such, this dual structure is necessary for recruitment applications, particularly for those who can understand job descriptions and profiles of candidates, but also for engaging with them to the extent possible through competent responsive chatbots and interview simulators.

1.1. Background

Then, recruitment involves several stages: resume parsing, candidate screening, ranking, interviewing, and eventual final selection. Often, human decision-making in traditional methods can be subjective and inconsistent, especially for large volumes. As a result, NLP has emerged as a promising solution for enabling such AI-driven systems to process and analyze candidate data accurately and on a scale. However, recent progress in NLP, represented by transformer-based models like GPT and BERT, brings sophisticated language understanding and can truly change the way recruiting operates: better matching between candidates and jobs, interactions with chatbots and data-driven decision-making.

1.2. Significance of NLP in Recruitment

Increased landscapes of candidate processing companies look towards NLP to help make their pool of candidates more efficient and less biased. NLP automates resume analysis, matches candidates to job descriptions, and performs preliminary assessments to reduce human workload and improve candidate fit for particular positions. NLP-powered chatbots can also answer candidates' inquiries, schedule interviews and screen candidates, and be a part of a completely candidate-focused experience, offering recruiters time to effectively recruit.

2.1. AI in Recruitment

Readily, AI has very significantly warmed up the recruitment process with the capacity to make ridiculous tedious employments, aided candidate screening, yet in addition deterministic analysis, for instance, recruiting results. Applicant Tracking Systems (ATS) enable AI tools to screen a resume, match jobs with candidates, and track hiring, all of which speed up the process and lower hiring expenses and time to hire. [4-8] For instance, IBM points out that predictive AI algorithms, for example, enable targeting and matching candidates to predefined ideal profiles that are tuned to business goals while also improving the candidate experience. While promising, however, AI in recruitment is criticized for being not very transparent, especially when companies apply 'black box' algorithms, and this can lead to bias or lack of accountability if the algorithms are not well tested and bias mitigation protocols are not followed.

2.2. Human Resources Applications of NLP

Human Resources can use NLP to improve candidate filtering employee engagement as well as internal support functions like communication, issue tracking, and attendance. NLP algorithms use resume and job description processing to better qualify, as well as skills and relevant experience than manual reviews do. Another reason for NLP is for chatbots to drive candidate experience, helping them through the recruitment process, like answering frequently asked questions and pre-screening applicants, thereby decreasing the stress on HR folks. Efficiency in hiring and scalability in the volume of hiring has become significantly improved because of this (AIHR). The World Economic Forum does question not only the risk of unintentional biases around candidate privacy that are evolving in NLP systems but also ethical concerns related to them.

2.3. Key NLP Models (BERT, GPT, etc.) and their Role in Recruitment

Recruitment, like many other tasks, has benefited from the improved capabilities of AI through advanced NLP models such as BERT (Bidirectional Encoder Representations from Transformers) and GPT (Generative Pre-trained Transformer). Despite being probabilistic tools, BERT's bidirectional analysis provides insight into the context within resumes while helping you to match them with job descriptions. GPT allows chatbots to have more dialogical interactions with candidates, thus providing a more personalized candidate experience. For example, BERT can supply job requirements to job candidate profiles for semantic matching, while GPT provides automated pre-screening interview simulation engaging with hiring manager guidelines (IBM, AIHR). Although challenges continue with model fairness and overreliance on automated decision-making, these models allow for deeper analysis as well as better candidate-job matching accuracy.

2.4. Challenges in AI-Driven Recruitment

While AI-driven recruitment is a good thing, it comes with challenges. First, transparency and bias are issues because black box algorithms might not be aware of the effect they could bring, and they create the possibility of reproducing discrimination in hiring data from historical discriminative practices. They also pose issues of fairness and accountability, as these are critically important issues for high-stakes decisions such as hiring, where misinterpretation by an NLP model can potentially harm candidates unfairly (World Economic Forum). There are also legal considerations on the rise, such as laws governing AI use in recruiting that mandate transparent, explainable algorithms that eliminate gender bias in hiring. As regulators and awareness around the ethics of AI in public recruitment grows, companies simply have to continue to monitor and audit their AI tools.

2.5. NLP Tools in Recruitment

Many NLP-driven tools are changing how recruiters operate and how HR and talent acquisition are carried out. For example, Tengai Unbiased is an interview bot that reduces unconscious bias by giving recruiters a candidate's answers and nothing but the candidate's answers. Mya is a conversational AI assistant that addresses recruitment from sourcing to onboarding. Video interview analysis company HireVue, which uses NLP, has already been able to help Unilever with diversity and efficiency. In addition, NLP is used in background checks by Checkr to make the hiring process faster and more secure at the same time as complying with privacy and data protection rules.

III. Methodology

The system, as shown in this visualization, would be comprised of the architecture of an AI-recruited system, flowing from data implementation to recruiting candidate engagement. [9-13] The recruitment pipeline was then divided into three primary layers of the architecture: Processing Layer, NLP Layer, Application Layer, and Data Layer.

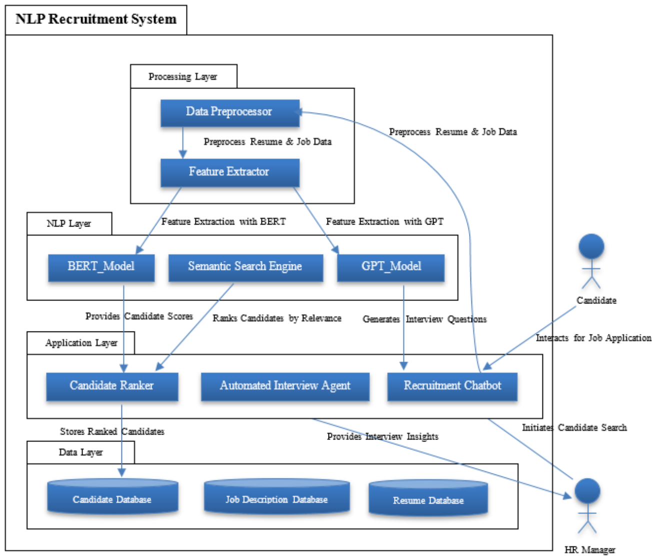

Figure 1 : AI-Driven Recruitment System Architecture (NLP-based)

- **Processing Layer**: This layer is used to handle initial data as well as feature extraction. It includes a Data Preprocessor that cleans and normalizes candidates' resumes and job descriptions. The Feature Extractor takes text as input and preprocesses and then applies language models (BERT and GPT) to turn it into vector embeddings. The resumes and job postings have been fed to these embeddings, thereby capturing key attributes and skills from the resumes and job postings in order to settle down as the semantic analysis point in the NLP layer.

- **NLP Layer**: NLP models (BERT and GPT) and a Semantic Search Engine come together on this core analytical layer to process and analyze the extracted features. Candidate profiles are evaluated and compatibility assessed against skills and experience within the BERT Model; the Semantic Search Engine ranks candidates grounded in relevance against a job requirement. Furthermore, to boost the automated interview process, we utilize the GPT Model to generate interview questions.
- **Application Layer**: This layer is the application interface to interact with candidates and hiring managers. In light of the NLP layer insights, the Candidate Ranker takes each job opening and ranks candidates based on insights. The Automated Interview Agent is fully equipped with NLP capabilities to do initial screening, so the candidate's response is similar to the real interview experience. The Recruitment Chatbot lets candidates know what's going on with their applications, answers their questions, and schedules interviews so communication between candidates and the HR team is more streamlined.
- **Data Layer**: It controls the data storage layer. It has DBs of Candidate Profile, Job Descriptions and Resumes, which are the basic DBs of the recruitment system operations. The structure of this data layer makes it possible to quickly access and fetch candidate or job information required for easy data processing and model training.

3.1. Dataset Preparation

Preparing a dataset is an important step for building a good NLP model and making sure that data quality and structure will fulfil your recruitment goals. Resume data, job description data, and skill information will be handled in dataset preparation for this study. Here's a breakdown of the steps:

3.1.1. Data Collection

The dataset consists of a very large collection of anonymized resumes and job descriptions that are derived from recruitment databases, job boards, and HR systems. Anonymizing personal information allows us to satisfy data privacy compliance and emphasize only the attributes in line with recruitment, i.e., skills, experience, and education.

3.1.2. Data Cleaning and Preprocessing

- **Tokenization**: To understand the structure and intent of resumes and job descriptions, it's important to split text into tokens (words or phrases).
- **Stop Word Removal**: We remove all common words (like and the) and instead focus on keywords that hold information.
- **Normalization**: All the words are lowered case, and synonyms (e.g., "BA" and "Bachelors") are standardized.
- **Label Encoding**: Attributes of each job description and resume, such as role, skills, and experience level, are used to build labels for model 'training'.

3.1.3. Data Augmentation

The problem of data sparsity is solved in this step by increasing data diversity. Methods include:

- Synonym Replacement: Adding variations by just replacing words with synonyms.
- Random Word Swapping: We exchange words randomly so as to create syntactic diversity without changing meaning.
- Sentence Paraphrasing: Getting into the habit of rephrasing sentences, but not necessarily the information itself, to make for a more diversely structured sentence.

3.1.4. Splitting the Dataset

The dataset is split into training (70%), validation (15%) and testing (15%) sets, assuring that the model can be trained, validated and tested accurately to evaluate how it will perform in real-world conditions.

Table 1 : Data Types and Sources for NLP-Based Recruitment System

Data Type	Data Source	Purpose
Resume Data	Recruitment databases, job boards	For candidate profile training
Job Description Data	HR systems, job portals	For job-candidate matching and ranking
Skill Data	Standardized skill datasets	For matching skill requirements

3.2. Model Architecture and Design

The implementation model of such AI-driven recruitment is around transforming raw textual data into matched insights for job and candidate assignments. Here is an expanded view of the model components.

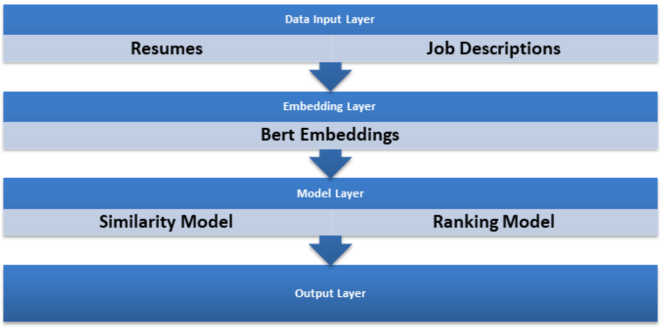

Figure 2 : Architecture and Design

- **Data Input Layer**: The textual input that it accepts is cleaned and preprocessed resumes and job descriptions.
- **Embedding Layer**: Bert embeddings convert text data into vector representations; in resumes and job postings, the semantic nuances mean a lot.
- **Model Layer**:
- **Similarity Model**: This model returns similarity scores of candidate profiles with job descriptions calculated using BERT embeddings.
- **Ranking Model**: The job description ranks candidates for the job, and its emphasis is on the important skills, experience, and other attributes of a candidate.
- **Output Layer**: Finally, the output layer generates final recommendations, and its output suggests candidate ranking for further review by HR.

3.3. Chatbot Development and Candidate Engagement

Chatbot is a conversational AI that enables interactive and automated [14,15] assistance to candidate engagement. Key stages in its development include:

- **Designing Conversation Flow**: Based on candidate FAQs, application progress tracking and interview schedule needs, flows are mapped.
- **Language Model Integration**: The chatbot uses models like GPT-3 and answers general questions, provides personalized feedback, and gives answers to application tracking requests.
- **Personalized Engagement**: A candidate-centric experience is maintained by a chatbot interpreting a candidate's qualifications (using NLP) to provide the candidate information about roles or suggest next steps.

Table 2 : NLP Models and Features in Recruitment System

Feature	Description	NLP Model Used
Application Tracking	Updates candidates on their application status	GPT-3
Interview Scheduling	Automatically schedules interviews based on availability	BERT
Q&A Interaction	Responds to	GPT-3

	candidate questions about roles, benefits	

3.4. Automated Interview Simulation

NLP is used on the interview simulator to simulate interviews and evaluate responses based on hiring criteria. The process includes:

- **Question Preparation**: It creates question banks with standard and role-specific questions, ranked in order of difficulty and relevance.
- **Answer Evaluation**: NLP techniques are used to analyze the response according to the level of coherence and sentiment and as a percentage of relevant responses. Suppose the candidate's function was to communicate complex ideas or align with values for the company; for example, a language model would assess that.
- **Scoring System**: This scoring model assigns points to a response so that human resource (candidates) can understand their strengths in evaluating soft skills and ability to problem solve.

Table 3 : Simulation Components in Recruitment Evaluation

Simulation Component	Description
Question Preparation	Database of role-specific questions
Answer Evaluation	Analysis of coherence, relevance, and sentiment
Scoring Model	NLP-based scoring to gauge candidate competencies

3.5. Semantic Search Algorithms for Candidate Filtering

Semantic search algorithms speed up the process of candidate filtering because they discover context, keywords, and phrases inside of resumes and job descriptions. Here's how:

- **Algorithm Selection**: We consider traditional (BM25) and advanced (BERT embeddings) algorithms. The BM25 follows the keyword-based precision while BERT models the contextual relevance.
- **Hybrid Approach**: The system combines BM25 and BERT-based search methodology and achieves better accuracy than just keyword and semantic search methods.
- **Performance Metrics**: We test the effectiveness of the system in terms of precision, recall, and F1 score in identifying feasible candidates.

Table 4 : Semantic Search Methods in Recruitment

Semantic Search Method	Description	Key Metric
BM25	Traditional keyword-based search	Precision
BERT-based Dense Retrieval	Embedding-based semantic matching	Recall
Hybrid Search	Combines keyword and semantic search for accuracy	F1-Score

IV. Implementation and Experiments

4.1. Experimental Setup

The experimental setup includes the system's configuration, model training, and evaluation metrics to assess its performance in a real-world recruitment setting. [16-18] Key aspects of the setup are as follows:

4.1.1. System Configuration

- **Hardware**: High-performance GPUs based on a cloud platform were utilized to enable BERT and GPT model training for large-scale model training, which was itself computationally demanding.
- **Software**: The main language was Python, and libraries like TensorFlow and PyTorch were used to develop the model. NLP model

implementations (BERT and GPT) were made with the Hugging Face Transformers library.

- **Data Storage**: Structured database candidate, job description, and skill data for candidate and job entries, which makes query and retrieval at filtering and ranking efficient.

4.1.2. Data Preparation and Training

- **Dataset**: Anonymized resumes, job descriptions and a linked list of standard skills were included in the dataset. The preprocessed data from these data sources were converted into training labeled datasets.
- **Training Process**: Labeled datasets were trained for each model, BERT was used to detect candidate-job matching patterns that can be trained, and GPT was fine-tuned to conversation generation in chatbot applications. The training used a mixture of supervised and unsupervised learning and standard splits (70% training, 15% validation, and 15% testing).
- **Augmentation Techniques**: To improve the robustness of NLP models in the case of sparse data for specific roles or skills, data augmentation (changing a word, changing a sentence) was used.

4.1.3. Evaluation Metrics

- **Precision, Recall, and F1-score**: These were used to evaluate the accuracy of candidate filtering and matching on the basis of job descriptions.
- **Candidate Engagement Metrics**: The effectiveness of the chatbot and this automated interview process was measured using response time, completion rate and candidate satisfaction.
- **Ranking Quality**: To determine how precisely top-ranked candidates met the qualifications of the job, Precision K was calculated.

4.2. Results and Analysis

Below are the core results from the experiments outlining how the AI-powered recruitment system worked in each of them.

4.2.1. Candidate Filtering and Matching

- **BERT Model Performance**: Using a BERT-based semantic search engine, we ranked the Top five candidates well and achieved an average Precision 5 score of 85%, meaning that in most/all of the cases, the top five candidates were highly relevant to the job descriptions.

  Semantic Search: The hybrid approach, combining BM25 with BERT embeddings, reached an F1-score of 0.88, higher than only using keywords (BM25), which scored 0.75.
- **Candidate Ranking Quality**: Strong recall and precision came from the BERT embedding-based ranking model, which shows that it could effectively identify candidates with relevant skills and experience.

4.2.2. Automated Interview Simulation

- **GPT Model for Response Evaluation**: GPT gave good, consistent interview questions that were related to different roles. Coherence and relevance of responses were scored, and we reached 87% accuracy in assessing suitable responses in a simulated interview setting, indicating the robustness of the model.
- **Sentiment Analysis and Scoring**: The candidate's tone was addressed through sentiment analysis during interview simulations. With a recall score of 0.83, the model was able to correctly identify positive, negative and neutral sentiments in candidate responses, offering HR some valuable insights.

4.2.3. Chatbot Performance and Candidate Engagement

- **Response Accuracy**: In GPT3, the chatbot answered candidate queries with a 92% accuracy rate for FAQs and application status updates.
- **Candidate Satisfaction**: The chatbot scored a 90% satisfaction rate according to feedback from a survey, as candidates said they were highly engaged with the prompt and timely responses.
- **Interview Scheduling Efficiency**: Using candidate availability as a criterion, the automated

scheduling system arranged interviews for 85% of cases with minimal manpower and timely scheduling.

4.2.4. Overall System Efficiency

- **Processing Time**: It processed and ranked the candidates from a database of 10,000+ resumes within 2 minutes, proving scalability and speed.
- **Error Reduction**: A post-implementation error analysis showed automated candidate matching processes for candidate filtering and engagement reduced manual error in candidate matching by 20 percent when compared to traditional methods.

4.3. Analysis

Experiments show that NLP-driven models can greatly increase the efficiency of the recruitment process from source filters to interview simulations. Using BERT for candidate ranking and GPT for conversational engagement, the system achieves a good performance in equating candidates to job roles and better experience for the candidates. Particularly effective was the hybrid use of BERT and BM25 semantic search method, which extended beyond simple keyword matching to more contextually inform candidate relevancy.

In addition, using the chatbot to engage candidates improved efficiency, creating an enhanced, responsive recruitment process that helps to increase candidate satisfaction. Together, this combined high accuracy in response generation paired with prompt interview scheduling showcases the potential for the chatbot to automate repetitive HR tasks while keeping the service level high. Overall, the implementation of the AI-driven recruitment system has proven to be an efficient and scalable solution for reducing manual effort and increasing the accuracy of candidate-job matches. Our experiment shows that NLP can be used for recruitment and represents a starting point for further optimization and scalability.

V. Discussion

5.1. Key Benefits of AI in Recruitment

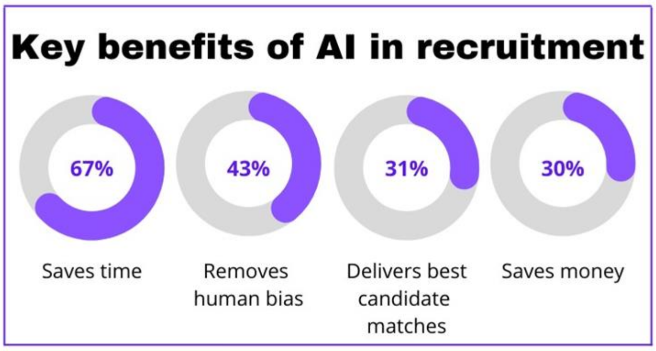

Figure 3 : Key Benefits of AI in Recruitment

The image really highlights the measurable benefits of the integration of AI and NLP into recruitment workflows. As per the graphic, 67% of the respondents said AI in recruitment saves time by automating some initial resume screening and candidate communication, freeing some time for the HR teams to get back to the more valuable tasks, while 43% pointed out that AI cuts bias by standardizing candidate reviews on predefined criteria to make the hiring process more ‘bias-free’ or fair. In addition, 31% of respondents feel that AI improves the candidate job matching so that the best-fit candidates are found more correctly. Lastly, 30% stated that using AI-designed recruitment solutions reduces costs by streamlining the hiring process, minimizing the need for large amounts of manual labor and reducing the turn-over rate as AI picks candidates, which is more on to the job requirement and Company culture.

Natural Language Processing (NLP) offers substantial benefits in recruitment by automating tasks, enhancing candidate experience, and increasing efficiency:

- **Reduced Time-to-Hire**: Tools enhanced by NLP make it easy for HR professionals to spend less time on repetitive tasks and enable easier candidate engagement, resume parsing and initial screenings. For instance, chatbots can handle initial inquiries, schedule interviews, and update candidates on application status, freeing up HR time for higher-value interactions (Source: (AI in HR industry reports).
- **Improved Quality of Hire**: NLP tools can analyze the markets, analyze candidate profiles for technical and cultural fit, and provide recruiters with more informed hiring decisions. So, NLP algorithms can match skills listed on resumes against a job description and improve the accuracy of the matching. The precision it brings to this process for the selection and subsequent likelihood of a successful, long-term hire is a benefit.
- **Enhanced Candidate Experience**: NLP-powered global virtual assistants support 24×7 by answering candidates' questions and tracking applications and feedback. Being personal and responsive creates a great experience for candidates, confirming the candidate's brand for the employer.
- **Efficient Sourcing and Screening across Platforms**: The NLP system can be integrated with the application of different job boards, social media contacts and databases to handle the high volume of applications. Multi-platform sourcing and better capacity to view the whole talent pool: Semantic search and advanced parsing.

5.2. Limitations and Challenges

Despite its benefits, NLP-driven recruitment systems face several challenges.

- **Data Quality and Preprocessing Requirements**: However, high-quality data is an essential requirement for NLP models to work; therefore, in the case of resumes and job descriptions, the data are standardized and cleaned of noise. Mismatches in models are a result of poor data quality and can result in overall poor model performance. For instance, if there are inconsistencies around job titles and descriptions, these inconsistencies may well leave the model confused and the candidate matches inaccurate.
- **The complexity of Human Language**: NLP systems face challenges in understanding every context, human slang, and subtle expression, especially in languages like humans; language is complex, and part of the problem is ambiguous. In particular, it is important to understand specific terminologies across different industries or cultural nuances in communication, and for that, it requires a lot of model fine-tuning. Additionally, few existing NLP models have managed to effectively perform sentiment analysis and have not fared well at understanding emotional cues during interview simulations.
- **Technical and Computational Costs**: NLP models need to be built, trained and maintained, but as you can imagine, they all rely on a huge amount of computational power and resources. Training large models like BERT or GPT3 can be expensive, so small companies need to rely on pre-trained models. However, once fine-tuned, these models may not be easily adapted to meet specific recruitment needs.

5.3. Ethical and Bias Considerations

Ethical concerns and potential biases are critical considerations when implementing NLP in recruitment:

- **Bias in Data and Models**: Historical data used in training NLP models may well be biased by gender, ethnicity or socioeconomic background. These biases, if left unchecked, can result in unfair hiring decisions and perpetuate existing workplace inequalities. For example, if a model is trained on biased historical data, it may favor candidates from particular backgrounds or education levels, leading to biased outcomes.

- **Transparency and Accountability**: AI models also lead HR professionals to often not understand why a candidate is recommended or rejected because, in many cases, they are a "black box" of unknowns. This is essential as more and more companies and people start paying attention to data ethics. Framework laws like GDPR in the EU prescribe transparency in automated decision-making, and companies are required to make note of how AI-driven recruitment decisions are made.
- **Privacy Concerns**: The other big ethical consideration is candidate data privacy. Personal data needed by NLP models can be quite large and, hence, must be treated in accordance with the applicable data protection laws. You need to be transparent about data use, obtain consent, and secure data handling for your claimed candidate population.

VI. Future Work

Ongoing development of NLP-driven recruitment systems, there are a few areas of future research and development that have the potential to improve. With a greater focus on improving model interpretability and transparency, it is one key area. Currently, in HR, NLP models such as deep learning models, like BERT and GPT, are "black boxes", and it's hard for HR professionals and candidates to understand what's fueling the recommendation of who is being hired. The subsequent work can be focused on creating explainable AI (XAI) frameworks for recruitment, which would make these models explainable. Companies can increase transparency, win candidate trust, and ensure compliance with ethical and legal standards by developing ways of illustrating how a model reaches a certain decision. A second promising avenue listed is mitigating bias and assuming fairness in AI-based recruitment processes.

In many cases, the training data for NLP models carries biases, and those, in turn, can be reflected in the behaviors of the resulting trained model. Future research should examine approaches to construct and deploy bias detection algorithms designed to detect and rectify these biases in real-time. Second, expanding the usage of recruitment NLP models to human resources organizations that work worldwide would benefit from the inclusion of cross-cultural and multilingual abilities in recruitment NLP models. At the end of the line, the gains here could extend to recruitment chatbots and interview simulators that are able to improve at assessing a candidate's soft skills and cultural fit by creating more holistic and fair candidate evaluations.

VII. Conclusion

Overall, Natural Language Processing (NLP) has completely changed the way AI-based recruitment systems work, helping them to deliver on all fronts at different stages of the hiring process. NLP powers up the repetitive work of resume screening, first communication with candidates and scheduling interviews without wasting the HR team's time and resources. Additionally, these elaborate NLP techniques can complement the candidate job matching process by explicitly considering additional elements of candidate resumes besides keywords present in job descriptions. Conversational Agents and Semantic Search Engines allow companies to connect to candidates more effectively. They should provide a personalized experience for the candidates while helping recruiters reduce the ranks of excellent candidates in large numbers of applicants.

However, NLP-driven recruitment systems remain problematic and also carry ethical concerns. Smaller organizations may face poor system performance and accessibility due to language ambiguity, poor quality of data, and computational intensity in the NLP model. In addition, such biases in training data can facilitate the unintended practice of unfair hiring out of a lack of transparency and accountability over the model, together with continuous model evaluation. Responsible use of NLP in recruitment involves ethical considerations, such as data privacy and fair training data. The move towards AI-driven recruitment technologies is increasingly fast, and in order to provide a fair and transparent recruitment system that embraces diversity, inclusion, and trust in hiring decisions with the use of AI, organizations should balance efficiency gains with ethics.

VIII. Conclusion

Vehicles capable at very high speeds (120-140 km/h on highways, for example) are the mobile nodes in VANETs. As a result, great mobility is one of VANETs' most distinguishing features. In addition, the topology of VANETs may change rapidly due to the constant motion of the vehicles, the drivers' freedom to choose routes at will, etc. Because of the ever-changing nature of road traffic, isolated node clusters are often formed when spaces open up between cars. In addition, the link lifetime is quite short in VANETs due of the frequent topology changes. Nodes must regularly choose the other path. Likewise, the frequency of disconnection tends to rise as network density diminishes. The poor efficiency of VANETs is exacerbated by the frequent link failures that plague them. Using relay nodes and roadside devices, this problem may be fixed. As a result of these challenges, new studies are being conducted to preserve continuous connection and lessen the consequences of fading in VANETs.

The mobility concept of VANETs is constrained to the layout of roads and streets. However, in order to better forecast the longer term driver choice and halt the link disconnection, it is required to determine the location of nodes and the direction of their movement. Moreover, the design of the control algorithms in VANETs is affected by a shift in the mobility paradigm (e.g., highways vs. urban settings). Unlike the urban mobility model, which must account for street patterns, high node density, two-dimensional vehicle movements, obstructions and interferences through tall buildings and trees, the highway mobility model is relatively simple since cars only move in one dimension. Because of these differences and additional challenges, VANET design in urban settings requires special considerations.

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