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Automated Resume Screening using Machine Learning

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Abstract: *Given the number of applications received for filling all vacancies, it becomes quite a difficult task in modern companies[cite: 3]. In case of manually screening applications for a particular job position, one needs plenty of time to spend on such a job, there is a possibility of human errors, as well as biases, that might cause the company choosing a candidate who is not suitable for the job position[cite: 4]. An automated Resume Screening System using Machine Learning techniques is a very good tool for solving this problem[cite: 5]. With its help, companies can filter through many resumes, obtain valuable information out of them, and even find out the degree to which candidates fit the particular job position by applying ad- vanced algorithms[cite: 6]. This paper discusses an automatic resume screening technique using machine learning, in which resumes are effectively screened and the applicants are ranked depending on their relevance towards job positions they apply for[cite: 7]. The proposed system uses Natural Language Processing and supervised models for identifying the applicant's skills, education, and other important features from the resume[cite: 8]. Later on, the algorithm finds out whether the candidate satisfies the requirements of the particular job position, giving each one a corresponding score[cite: 9]. The use of automation reduces the time taken in recruiting process, saves effort, and ensures fairness in candidate selection[cite: 9].*

Keywords: Automated Resume Screening, Machine Learning, NLP, Recruitment Automation, Resume Categorization, Candidate Evaluation, Feature Identification, Intelligent Recruitment System [cite: 10]

I. INTRODUCTION

Modern organizations receive numerous resumes for each job position that is available[cite: 11]. Manual resume screen- ing by human resource managers has become challenging in recent years due to the overwhelming number of applications and shortage of time[cite: 13]. The process of manual resume screening takes plenty of time and effort[cite: 14]. Addition- ally, manual resume screening can bring some personal biases into the evaluation and thus reduce the effectiveness of the hiring process[cite: 15]. With the growth of businesses moving the recruitment process online, intelligent resume screening systems have become necessary[cite: 16]. Incorporation of machine learning for the automatic screening process of resumes has become an effective way of addressing these challenges[cite: 17]. The machine learning model analyzes the content of the resumes and then matches the required skills to job descriptions[cite: 18]. This process involves natural language processing to generate structured data from unstructured resumes[cite: 19]. The automatic screening system ranks the candidate on the basis of their suitability for the position using the resumes' machine-readable feature extraction process[cite: 20].

The traditional resume screening approach includes the use of keywords or rules to filter out resumes that do not match the positions[cite: 21]. However, the process does not analyze the context and therefore misses out potential candidates who might have used different wording techniques[cite: 22]. The rule-based model requires manual setting-up processes that cannot effectively adapt to changes in the job requirement specifications[cite: 23]. Considering all the above factors, intelligent machine learning models must be applied[cite: 24]. Advances in deep learning and machine learning algorithms can help automate the resume screening process[cite: 25]. One can implement SVM, Random

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Forest, Naıve Bayes, and Deep Learning techniques to categorize resumes based on job types[cite: 26]. In addition, one can apply similarity-based resume ranking algorithms such as TF-IDF, Word embedding, and transformers to enable the process of identifying jobs for different candidates[cite: 27]. The use of such technologies will assist companies in handling big data sets and minimizing time wasted on manual resume screening processes[cite: 28]. Moreover, an automated resume screening process will enable organizations to hire candidates in an unbiased and efficient way since it eliminates biases associated with people[cite: 29]. Contrary to people, machine learning models lack pref- erences while analyzing candidates' qualities and skills[cite: 30]. Therefore, recruiters will effectively filter candidates using intelligent ranking algorithms[cite: 31]. Hence, the entire hiring process will become fast and efficient due to resume screening automation[cite: 32]. This project intends to develop a system that automatically screens resumes using machine learning models to determine essential components of resumes, filter resumes, and rank them according to the job position's requirements[cite: 33].

II. RELATED WORKS

The recent research on Automated Resume Screening mainly focuses on improving the efficiency of the recruiting process using machine learning and natural language processing techniques[cite: 35]. Several researchers have looked into the process of automated resume screening in which candidate profiles are classified according to the job description[cite: 36]. The use of text mining approaches helped in the extraction of relevant information such as skills, educational details, and experiences from resumes[cite: 37]. Then this information is used for training machine learning models to sort and rank the candidates[cite: 38]. Various machine learning models have been used for automated resume screening[cite: 39]. Machine learning classifiers such as Na¨ıve Bayes, SVM, Decision Trees, and Random Forest have no been employed to classify resumes according to the job description[cite: 40]. This im- proves the filtering process in an automated way through which the appropriate candidates can be automatically filtered[cite: 41]. Similarity-based matching approaches such as cosine similarity and TF-IDF vectorization have been largely used to match resumes and job descriptions[cite: 42].

In recent times, the focus of the studies has been on the resume screening tools that make use of deep learning techniques[cite: 43]. The neural networks along with the transformer models have been used to decipher the meaning of resumes[cite: 44]. Techniques such as Word2Vec, GloVe, and BERT help to match the meanings of the resumes and hence provide greater accuracy in ranking[cite: 45]. They are more reliable than the keyword matching techniques[cite: 46]. Some studies have also recommended an end-to-end automated re- cruitment framework with the use of modules such as resume parsing, candidate classification, and candidate ranking[cite: 47]. Such frameworks automatically extract the information from the resumes and store them in the databases for future analysis purposes[cite: 48]. Some other research papers have even considered the use of recommendation systems to choose candidates for certain positions[cite: 49]. However, there are a number of issues concerning the existing resume screening procedures[cite: 50]. The excessive dependency on keywords will lead to wrong filters being used[cite: 51]. Some models demand a large amount of annotated data sets for training; sometimes, it may not be possible[cite: 52]. In addition, skewed data sets can harm the objectivity of the screening process[cite: 53]. Also, developing intelligent systems able to parse resumes of diverse format and evolve as a company matures will have to be taken into account[cite: 54]. In order to bridge the gaps, intelligent machine-learning-based systems which are able to learn about context, adjust to changes within the labor market, and develop better processes for ranking candidates should be developed[cite: 55]. The aim of this research is the development of an intelligent system using machine learning algorithms to process resumes[cite: 56].

III. LITERATURE REVIEW

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The following table[cite: 58]:

TABLE I: LITERATURE REVIEW SUMMARY TABLE [CITE: 58]

Sr. No	Title (Year)	Focus Area	Methodology	Dataset	Key Results	Challenges
1	CNN-GRU Ranking (2025) [cite: 58]	Resume scanning and ranking [cite: 58]	CNN and GRU sequence handling [cite: 58]	Recruitment datasets [cite: 58]	Better ranking precision [cite: 58]	Large labeled data; complexity [cite: 58]
2	Emotion Detection System [cite: 58]	Emotion detection capabilities [cite: 58]	ML with emotion detection [cite: 58]	Resume/emotion dataset [cite: 58]	Emotional intelligence [cite: 58]	Privacy issues; low accuracy [cite: 58]
3	Resume Analyzer NLP (2024) [cite: 58]	Information gathering [cite: 58]	Tokenization, entity recognition [cite: 58]	Resume/job descriptions [cite: 58]	Candidate info extraction [cite: 58]	Limited semantic analysis [cite: 58]
4	Recommendation System (2025) [cite: 58]	Skill recommendation [cite: 58]	Multi-Field CNN [cite: 58]	Recruitment process data [cite: 58]	Enhanced job recommendations [cite: 58]	Need of large data [cite: 58]
5	Transformer Networks (2025) [cite: 58]	Semantic ranking [cite: 58]	Transformers; Learning-to-Rank [cite: 58]	Recruitment data sets [cite: 58]	Increased matching accuracy [cite: 58]	Complex algorithms; costs [cite: 58]
6	AI in Recruitment (2025) [cite: 58]	Selection automation [cite: 58]	ML approaches [cite: 58]	Experimental datasets [cite: 58]	Fastened hiring process [cite: 58]	Biasness;data privacy [cite: 58]
7	Semantic analysis NLP [cite: 58]	Resume processing [cite: 58]	spaCy, custom extraction [cite: 58]	MongoDB clusters [cite: 58]	92.82% precision [cite: 58]	Support for diverse formats [cite: 58]
8	Efficient Automation (2024) [cite: 58]	Screening purposes [cite: 58]	ML and NLP assessment [cite: 58]	Resume/recruitment data [cite: 58]	Screening improvements [cite: 58]	Privacy and accuracy issues [cite: 58]
9	Interaction Learning (2020) [cite: 58]	Recommendation [cite: 58]	Multi-field CNN interactions [cite: 58]	Recruiter behavior dataset [cite: 58]	Enhanced click-through rate [cite: 58]	Requires big behavior data [cite: 58]
10	SATYA Analyzer (2024) [cite: 58]	Talent yield analysis [cite: 58]	Graph-based, NLP, ML [cite: 58]	1000 resumes (HR professionals) [cite: 58]	91.4% screening precision [cite: 58]	System complexity [cite: 58]
11	AI Efficiency Assessment (2025) [cite: 58]	Efficiency evaluation [cite: 58]	Precision and re-call benchmarking [cite: 58]	Extensive resume databases [cite: 58]	Accuracy and speedup [cite: 58]	Scaling application [cite: 58]
12	Predictive Analytics	Recruitment decisions	AI and predictive	Hiring history databases [cite:	Improving Recruitment	Reliable data/models

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	(2025) [cite: 58]	[cite: 58]	analytics [cite: 58]	58]	quality [cite: 58]	[cite: 58]
13	ML Methodology CV (2024) [cite: 58]	Automatic matching [cite: 58]	Supervised learning classification [cite: 58]	Annotated CVs dataset [cite: 58]	Job profile accuracy [cite: 58]	Variety of resumes formats [cite: 58]
14	Selection via Parsing (2025) [cite: 58]	Resume parsing tool [cite: 58]	NLP parsing and ML classifying [cite: 58]	Unstructured documents [cite: 58]	Efficient extraction/filtering [cite: 58]	Noise and parsing errors [cite: 58]
15	KSA Parameters (2025) [cite: 58]	Automated KSA screening [cite: 58]	NLP and ML algorithms [cite: 58]	Resumes/job descriptions [cite: 58]	Candidate-job alignment [cite: 58]	Accurate KAS extraction [cite: 58]

• **User Interface Layer**: interaction between the users and the system; recruiters upload job descriptions and applicants upload resumes[cite: 78, 79, 80].

• **Data Collection & Preprocessing Layer**: Includes noise elimination, tokenizing/normalizing text, eliminating stop- words, and extraction of features[cite: 81, 83, 84, 85, 86].

• **Deep Learning Prediction Engine**: Core where deep learning models like CNN, RNN/LSTM, and Transform- ers are employed for feature extraction and compatibility calculation[cite: 88, 89, 91, 92, 93].

• **Database and Storage Layer**: Enables efficient data access, scalability, and analysis of historical data[cite: 94, 96, 97, 98].

• **Feedback and Learning Layer**: Ensures continuous evo- lution and improvement through recruiter interaction[cite: 99, 100]

IV. OPTIMIZATION, SUSTAINABILITY, AND INTEL- LIGENT RESOURCE MANAGEMENT

The concept of automatic resume screening with machine learning technology has been an important aspect of re-cruitment in recent years[cite: 60]. Traditional recruitment techniques involve resume screening, which involves a con-siderable amount of time and human error[cite: 61]. These issues have been overcome with the advent of automatic resume screening[cite: 62]. The efficiency aspect of machine learning algorithms comes into play when optimizing for speed of resume screening[cite: 62]. Machine learning techniques such as NLP, classification, and semantic analysis enable a recruitment algorithm to gather vital information such as candidates' skills, educational qualifications, work experience, and relevant keywords from their resumes[cite: 63]. Such gathered information can then be compared with that of the required job description to accurately rank applicants[cite: 64]. Efficiency through machine learning involves improving accu- racy of the algorithm while reducing computational effort[cite: 65].

The idea of sustainability in automated resume screen- ing revolves around cutting the cost of resources used and increasing efficiency in the long run[cite: 66]. Like other sustainable computing technologies, ML-based technologies are oriented towards minimizing unnecessary computations and optimizing performance without increasing manual in-tervention[cite: 67]. Efficient algorithms and well-optimized ML models lead to increased efficiency of the recruitment process by decreasing the cost of computation[cite: 68]. It is important to have an effective resource management system for managing recruitment data efficiently at scale[cite: 69]. Computational resources in ML-based technologies adapt to the workload and demand, which helps process the information about candidates more efficiently when the load is high[cite: 70]. Prediction technologies predict the demand and adjust the resources appropriately to ensure proper performance of the system[cite: 71]. Finally, many modern ML models also have feedback mechanisms that improve model performance over time[cite: 72]. As models gain new knowledge through their interaction with

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recruiters and hiring data, they are able to make increasingly accurate predictions[cite: 73]. At the same time, the problem of bias, transparency, and decision-making fairness remain important research questions[cite: 74].

V. PROPOSED ARCHITECTURE FOR DEEP LEARNING-BASED AUTOMATED RESUME SCREENING

The architecture designed to automate the processing of resumes using deep learning should help achieve accuracy, scalability, and intelligence in candidate evaluation[cite: 76]. The architecture comprises the following components that perform various tasks in the process of resume processing and feature extraction[cite: 77]:

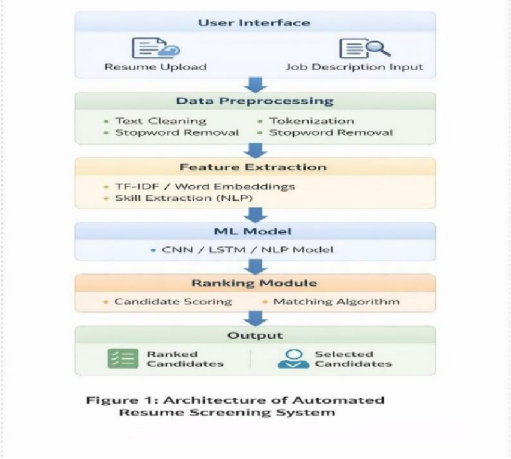

Figure 1: Architecture of Automated Resume Screening System.

VI. METHODOLOGY

The purpose of the presented methodology is to implement machine learning and NLP solutions for improving the resume screening process[cite: 103]. The purpose in this case would be making the hiring process faster and more efficient, excluding any extra work involved in matching applicants and vacan- cies[cite: 104]. The following stages of this process include data gathering, data pre-processing, feature selection, model building, ranking of applicants, and process optimization[cite: 105]. Initially, the data is obtained from various sources like job websites, database of a particular company, and applicant tracking systems[cite: 106]. Resumes can be in different formats like PDF, DOCX, and TXT files[cite: 107]. A resume parser will take all necessary information like the candidate's name, education, skills, work experience, and others[cite: 108]. After getting the necessary data, one will perform the next step, which implies data preprocessing[cite: 109]. Here you will have to remove any useless elements from your dataset like some irrelevant characters, stop words, and redundant information[cite: 110]. NLP will involve steps like tokenizing the data, performing stemming, lemmatization, etc[cite: 111]. This is when the Learning stage comes into play and implies applying the machine learning algorithm to the labeled dataset[cite: 112]. Simply put, we are building a machine learning model that will demonstrate the dependence be- tween resume characteristics and job characteristics[cite: 113]. Thanks to this, it will be possible for the machine learning algorithm to make an evaluation and assessment of how relevant this resume will be to the required position[cite: 114]. As for candidate ranking, it means evaluating each particular applicant[cite: 115]. Candidates are ranked by how well they fit the requirements that have been specified in the resume[cite: 116]. In this way, it will become easier to find out the most appropriate candidates and thus considerably save time on the recruitment process[cite: 117]. The feedback loop implies updating the machine learning model on the basis of the decision made by recruiters[cite: 118].

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VII. EXPECTED OUTCOMES AND FUTURE WORK

The proposed technology would make use of ML and NLP, thus making the process of attracting people much easier[cite: 120]. Firstly, it would automatically filter out the most suitable candidates from large amounts of resumes submitted[cite: 121]. Secondly, as a result of using this algorithm, we are guaranteed to have a bias-free recruiting process since there Lastly, in terms of assessing the efficiency of the technology, its application in real-life recruiting processes and integration with appli- cant tracking systems can become the best way forward[cite: 125]. Certain performance metrics such as accuracy, precision, recall, and processing time might serve as an indicator of efficiency[cite: 126].

VIII. CONCLUSION

In regards to further advances in this domain, one can consider employing deep learning approaches, which may be rather helpful in this case[cite: 128]. For instance, BERT can be taken into account[cite: 129]. Taking into account the fact that the number of CVs increases exponentially, recruiters will find themselves dealing with increased time and efforts spent on reviewing them[cite: 129]. Furthermore, this task involves not only higher demands in terms of time and efforts but also makes recruiters vulnerable to potential biases[cite: 130]. As such, the implementation of a machine learning based resume review technology should be considered as a viable option[cite: 131, 132]. Moreover, this procedure not only requires additional efforts but also exposes those who conduct the process to the risks of being influenced by the bias[cite: 133].

Hence, the utilization of an automated resume screening technology utilizing machine learning could be regarded as a feasible solution to the identified issue[cite: 134]. The purpose of the current study includes the application of a machine learning-based resume screening process[cite: 135]. Namely, the framework will include the utilization of resume parsing, NLP, feature extraction, and developing predictive models that would enable recruiters to determine the most suitable candidates based on the comparison between their skills and the available jobs[cite: 136]. Among other distinctive aspects of the technology under discussion, there is a possibility to improve its functioning in a continuous manner[cite: 137]. It can be reached owing to the process of feedback provided by recruiters which allows enhancing its performance through training[cite: 138]. Therefore, machine learning as well as NLP in resume screening can help make this process effec- tive[cite: 139].

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Volume 6, Issue 9, April 2026
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