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DETECTION OF JOB AND CANDIDATE FINDING SOLUTION USING AI

A.Haseena[1]., S.Ashwathi[2]., P.Maheshwari[3]., K.Varsha[4]., K.Harika[5]

1 Assistant Professor, Department Of ECE., Malla Reddy College Of Engineering For Women., Maisammaguda., Medchal., Ts, India (✉haseenamtech007@gmail.com)

2,3,4,5 B.Tech ECE, (19RG1A04B8, 19RG1A04B0, 19RG1A0487, 19RG1A0489),

Malla Reddy College Of Engineering For Women., Maisammaguda., Medchal., Ts, India

Abstract. In order to bridge the gap and improve the efficiency of the extensive hiring procedures, AI-based solutions have shown to be quite useful. Recent innovations have shown the critical importance of gamification in management processes more generally, and in recruitment in particular. The use of AI as a solution to the difficulties of the employment process is at odds with itself in a number of ways. This study first examines the pros and cons of using AI for hiring, then proposes a model for doing initial resume screening using keywords and phrases against the job description. Additionally, the outcomes and consequences of using AI-based technologies, namely machine learning models, in a straightforward employment scenario have been presented and evaluated.

1 Introduction

When it comes to hiring new staff, human resource management (HRM) is always on the lookout for cutting-edge tools to streamline the process. With the use of new technologies, it has been able to digitize formerly analog processes, such as the application and interviewing phases of the hiring process[1]. Different researchers and writers are now describing and understanding the use of AI technologies in recruiting and selection operations as a rising trend that has offered new potential and difficulties for business cases. One of the most significant developments in HRM is the use of artificial intelligence. Human resource management (HRM) has benefited from AI, and more especially the subset of AI known as Machine Learning, which has allowed for the automation of formerly manual processes such as fundamental and significant aspects of recruiting and selection[2, 4].

1.1 Theoretical background

Human resource management is always on the lookout for cutting-edge tools that may streamline the selection and hiring processes. HRM has been able to automate certain formerly manual parts of the hiring process thanks to recent technology developments [3]. Finding and recruiting individuals online has introduced new dynamics to the hiring process. One of the most often used forms of online recruiting nowadays is sourcing via social media. Companies often utilize social media sites like Facebook, LinkedIn, Glassdoor, and Instagram to advertise open positions and find qualified applicants. It's a powerful method to increase the company's favorable reputation and attract top talent.

Organizational homepage. It offers details about fresh employment prospects in

the organization is accepting applications and collecting data from interested parties.

Websites that list available jobs. Human resources departments post job openings on websites where prospective employees may also look for work.

Online chats and meetings. HRM may conduct interviews with prospective applicants remotely because to video conferencing tools like Skype, Teams, Zoom, and G-meet.

– Software with built-in AI. Human intelligence-based software that streamlines and expedites the HRM recruiting process from candidate discovery and screening to offer acceptance and onboarding.

Today, the application of AI in recruiting processes is a major development and trend in human resource management. Human resource management may now use AI to automate formerly manual processes like applicant screening and candidate vetting. Seventy percent of businesses will use AI by 2030, according to [5], and nations that become global leaders in AI may see their economies grow by as much as 25 percent.

1.1.1 Artificial intelligence - its use in the recruitment process

Artificial intelligence (AI) is a branch of computer science concerned with teaching machines to carry out work originally intended for humans. Natural human intelligence is compared to artificial intelligence in an effort to mimic and, by extension, increase human intellect. Using computational intelligence behavioral models, the field of neuroscience aspires to create artificial intelligence capable of thinking, learning, decision-making, and executing complicated tasks in the same way as the human brain does [6, p.]. Over the last several years, the influence of AI in the hiring process has grown at an unprecedented rate. The massive software available in the modern recruiting market, which uses AI-based solutions, greatly aids companies in reducing the workload associated with the whole recruitment process. Modern AI systems can perform a variety of tasks. Particular areas where AI has proven useful in the HR process include: candidate sourcing; engagement candidate tracking; CV screening; pre-employment assessments; video interviews; etc. Robotic process of hiring entails many technologies used at various stages of the hiring procedure [7].

Using AI-powered solutions, businesses can quickly sift through a large pool of resumes to find the most qualified employees. In fact, it's one of the most popular AI-powered methods of finding new employees [7]. When it comes to the selection process and the entire employer experience, the use of AI in recruitment has totally rewritten the rules. Chatbots are an example of an AI technology that is giving job seekers and employers alike a leg up. Applications infused with AI can easily manage the whole of the assessment process, including the scheduling of interviews, the creation of personalized applicant profiles, the creation of personalized offers, and the verification of references. Despite AI's widespread adoption, just 10% of businesses are making extensive use of it as now, while 36% of businesses plan to do so in the near future [8]. The following are examples of well-known AI applications that large corporations have implemented:

- Applicant Tracking Systems (ATS) and Customer Relationship Management (CRM) Systems Applicant Tracking Systems (ATS) - platforms that provide recruiters the opportunity to monitor the whole employment process, from the first point of contact to the final offer.

Management of Interactions with Job Seekers (CRM)

Screeners of Resumes and Curriculum Vitae

- Intelligent Chatbots Find some chatbots and put them to work for you.

- Tests Done Before Hiring Someone

AI-driven job interviews

Artificial intelligence (AI) driven recruiting technology solves the problem of massive amounts of data with tools like resume scanners. Keywords and primary phrases that are fundamental to the criteria are used by trained models to filter and identify the features in the provided information. Chatbots, on the other hand, are programmed to act like humans in conversations by analyzing user input and providing appropriate responses using natural language processing (NLP) techniques. Standardized method is used with facial expression analysis, language analysis, and nonverbal measurement in AI-powered interviews [9].

Humans have a high opinion of the efficacy and objectivity of AI-powered recruiting solutions. While AI has the potential to greatly improve the recruiting process, differing opinions exist on whether or not it is really useful for this purpose [7]. Researchers have shown records of erroneous outcomes, and there are difficulties with the disability problem, which raises doubts about the usefulness of AI in the recruiting procedures. The evaluation of fairness for people with disabilities has received very little consideration. Putting aside the effects of AI, the institutional barriers that hinder persons with disabilities from finding and keeping a job are a serious, continuing problem. Therefore, adding layers of complexity to the system of automated evaluation of applicants increases the potential for damage [10]. Recruiters can easily identify applicants and collect character data thanks to the use of AI into commercial tactics. The recruiters are now free to focus on more strategic matters after automating the mundane jobs and replacing them with real people.

While AI is intended to eliminate bias in the hiring process, even the most well-intentioned methods aren't immune to the prejudices of their creators. It's unclear how this will alter the fundamental tasks of recruiting AI systems, and there are numerous open concerns. Accordingly, if
Name, age, gender, etc. are all examples of highly biased data that may be filtered out with the use of AI[8], [11], [12].

Contrary to popular belief, multiple academic studies have shown that AI recruitment does not automatically violate human rights[13]. However, whether or not ethical values are compromised by the usage or training of AI technologies is largely context dependent. Human rights concerns and duties in the context of AI hiring are, nevertheless, of the utmost significance [8]. There is now a new void that has to be filled by further study and standards, joining the problem of bias in AI techniques.

The vast majority of businesses who use AI for recruitment have no idea how to really put it into practice. Before using AI-based solutions, it is crucial to first identify certain subsets of the talent pool. Artificial intelligence techniques are used as low-cost alternatives in large-scale application contexts [14].

In addition to saving money, AI may improve other aspects of the hiring process, such as the review, processing, ranking, qualification screening, elimination of administrative and routine duties, communication, and overall speed. Most importantly, in a biased situation, AI ensures that all qualified applicants are given a fair shot, eliminating any potential for favoritism. The use of AI technologies has an effect on a company's competitiveness [6], while also providing valuable information into its talent acquisition strategy.

2 Proposed Methodology

In the theoretical section of the study, we defined e-recruitment and AI with their personalities using articles and research papers written by a variety of writers and researchers. We used deductive and analytical techniques to test hypotheses, sort through data, and clarify the interplay between e-recruitment and AI. We used deductive and inductive reasoning to examine and synthesize the available literature and discovered very little information on the potential effects of AI-based solutions on the recruitment process[15].

As part of our analysis of the state of the art in the subject, we have compiled a summary of research gaps and current challenges in an effort to address the following research questions:

What does the future hold for AI-based solutions in the HR department?

To what degree may the performance and outcome of the screening process be impacted by the machine learning models?

As such, this study's overarching objective is to respond to the mentioned research questions by looking into and analyzing the outcomes of AI-based solutions used in the hiring process. In particular, the significance of processing resume datasets in a timely and effective manner.

In the study's applied section, we put into place a basic model for resume screening using machine learning; this model is predicated on text categorization and keyword similarities discovered inside resumes or applicant profiles, expanding upon the discussion presented above. The ease with which a resume can be read is another factor that might speed up the selection process. To this end, a readability score has been suggested as a measure of screening and categorization. This research makes use of the dataset provided by

Kaggle.com [16] has a "Resume dataset" with more than 2,000 resumes for a wide range of positions and specialties.

Table 1 Dataset used to train the model.

Label	Description
ID	Unique identifier and file name for the respective pdf.
Resume_html	Contains the resume data in html format as present while web scrapping.
Resume_str	Contains the resume text only in string format.
Category	Category of the job the resume was used to apply.

The dataset is separated into training and test sets by a 75/25 split, respectively. After importing relevant modules, and loading the dataset, a pre-processing of the data was conducted, using stemmer function from nltk library, namely, Porter Stemmer[17] Algorithm as a text normalizing algorithm.

Table 2 The pre-processing of data

Function	Description
Stop words	Tokenizing the input words into individual tokens and stored it in an array. StopWords [8]
Tokenization	Converting the corpus to a vector of token counts. Count Vectorizer (sklearn)
Lemmatization	Transform the corpus of text into a list of words and assign words to lemmas.

Table 2 shows that the data was cleaned, tokenized, stemmed, and lemmatized during the pre-processing step, which was necessary because of the significance of the dataset. All words were changed to lower case so that case wouldn't be taken into account, and a custom blacklist of terms was used to filter out those with low semantic load from the natural language toolkit (nltk) package. The stemmer-function in the 'nltk' library was found to be quite useful for preventing the dictionary from being bloated with several variants of the same word and for improving overall accuracy.

Implementation and results

The suggested method employs a number of strategies to achieve automated screening of candidates' resumes, with a primary emphasis on the resume's content, namely its keyword use. For this reason, keyword extraction is part of the feature extraction stage, and similarity calculation is part of the stage after that. In the extraction phase, we take the company's job description and use it to determine which keywords, phrases, and relevant parameters to extract..

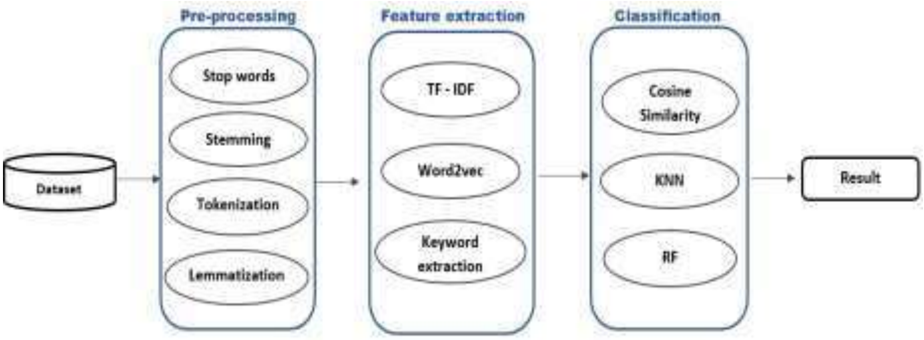

Figure 1 The architecture and activity overflow of the implemented model

The three steps of the proposed model's architecture—pre-processing, data extraction, and final classification—are shown in fig. 1.
Tf-Idf. Tf-idf was utilized to determine significance in the second stage. Each word in a document is given a weighted score based on how often it occurs in the text [18–20]. Next, we standardize this measure by dividing it by the total number of words in the set. When you take into account the fact that shorter words tend to have greater significance. In addition, the inverse document frequency rates the words in relation to the specified section based on their uniqueness. This means that words are organized according to how often they appear in a certain portion of text, rather than alphabetically.

.

```
wordfrequencydist = nltk.FreqDist(total_Words)
mostCommon = wordfrequencydist.most_common(50)
print(mostCommon)
from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import TfidfVectorizer
from scipy.sparse import hstack
required_Text = resumeData['structured_resume'].values
required_Target = resumeData['Category'].values
word_vectorizer = TfidfVectorizer(sublinear_tf=True,stop_words='english',max_featu
res=1500)
word_vectorizer.fit(required_Text)
WordFeatures = word_vectorizer.transform(required_Text)
```

Figure 2 Feature extraction and vectorizing

Word2Vec. Because our model relies heavily on the connections between words, the Word2vec model proved to be a practical option. To handle text, word2vec is the most widely used word embedding model approach. The key to its success is its capacity to cluster word vectors with comparable meanings[21]. You may use either a Skip-gram or a Common Bag of Words to construct a word2vec model. While the Common Bag of Words uses the context of the words to forecast the target word, the skip-gram model uses the target word to predict its surroundings.

Figure 3 Keyword generating and printing after extraction phase

```
wordscores = Calculate_Word_Scores(phraseList)
keywordresume = Generate_resume_Keyword_Scores(phraseList, wordscores)
sortedKeywords = sorted(keywordresume.items(), key=operator.itemgetter(1), reverse=True)
totalKeywords = len(sortedKeywords)
rake = Rake("db\\Stop_Word_List.txt")
keywords = rake.run(text)
print (keywords)
```

K-nearest neighbors algorithm (k-NN). Nearest neighbors is a supervised learning model which is used for classification and regression analysis[20]. KNN does not have parameters we can change or optimize in order to achieve better performance. This model is used to identify the resumes that are nearest matching the given job description. First, to have similar parameter the open-source library “gensim” was taken into account, generating so the summary of the provided text in the provided word limit.

Final output on running similarity on words and phrases, with the percentage score reached against parameters defined.

```
# import cosine similarity
from sklearn.metrics.pairwise import cosine_similarity

#similarity score
matchpercentage = cosine_similarity(count_matrix)[0][1]
matchpercentage = round(matchpercentage*100,2)
print('Resume matches {} % score to job description! ',cosine_similarity(count_matrix))
```

```
Resume matches 83.26 % score to job description!
```

Figure 4 Cosine similarity output

Because determining how well a resume matches a job description is the model's primary purpose, the cosine similarity is being used here as the similarity metric. Cosine similarity is used to compute the degree of similarity between two vectors by measuring the cosine of the angle between them. The 0 and 1 count matrices were verified in our scenario. values, was put into place to compare similarities and have the final result shown as a percentage on the applicant's profile page.

Conclusion

In the theoretical section, we utilized deduction and analysis to screen, filter, and define current information before explaining e-recruitment and AI, as well as their interrelated qualities, components, principles, and prospective advantages. We utilized deductive and inductive reasoning to analyze and synthesize current information and knowledge to identify a knowledge gap on the implications of AI-based solutions in the recruitment process.

We found that using AI-powered software in the recruitment process can cut down on the time it takes to screen and shortlist candidates by looking for relevant keywords in resumes and then comparing and matching those keywords to the requirements of open positions. Reduces the effects of human prejudice such as the "similarity attraction effect," "confirmation bias," "halo effect," "demographic discrimination," and "others," allowing for a more objective and fair hiring process. Nevertheless, in terms of model training and parameter tuning, machine learning models can only be as good as human. The implications for the advancement of science and scholarship are enormous, since human bias may be transmitted inadvertently to the AI-based model.

Although AI-based models have the potential to improve recruiting process efficiency and effectiveness, they are not without their own set of constraints and hurdles. There are a number of factors that must be taken into account and supported, including but not limited to: programming restrictions, the capacity to inherit human bias, certain dependencies, a lack of human judgement, and a lack of knowledge. Our primary objective was to investigate and explore the consequences of using AI-based solutions in the recruitment process, and through addressing research questions, we have done just that. In particular, the significance of processing resume datasets in a timely and space-efficient manner.

Although a wealth of data and insights have been made available, there are still several roadblocks to putting our findings into practice. We narrowed down on the candidate's profile by analyzing just the skill characteristic and the keywords found in the résumé. Other characteristics of the candidate's profile, such as the sentiment score of the material as a whole, might be taken into greater account in future research by combining sentiment analysis with the notion of recommendation systems.

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