Enhanced Resume Screening for Smart Hiring Using Sentence-Bidirectional Encoder Representations from Transformers (S-BERT)

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Abstract—**In a world inundated with resumes, the hiring process is often challenging, particularly for large organizations. HR professionals face the daunting task of manually sifting through numerous applications. This paper presents 'Enhanced Resume Screening for Smart Hiring using Sentence-Bidirectional Encoder Representations from Transformers (S-BERT)' to revolutionize this process. For HR professionals dealing with overwhelming numbers of resumes, the manual screening process is time consuming and error-prone. To address this, here the proposed solution is developed for an automated solution leveraging NLP techniques and a cosine distance matrix. Our approach involves pre-processing, embed- ding generation using S-BERT, cosine similarity calculation, and ranking based on scores. In our evaluation on a dataset of 223 resumes, our automated screening mechanism demonstrated remarkable efficiency with a screening speed of 0.233 seconds per resume. The system's accuracy was 90%, showcasing its ability to effectively identify relevant resumes. This work presents a powerful tool for HR professionals, significantly reducing the manual workload and enhancing the accuracy of identifying suitable candidates. The societal impact lies in streamlining hiring processes, making them more efficient and accessible, ultimately contributing to a more productive and equitable job market.**

Keywords—S-BERT; resume; automated screening; job; CV

I. Introduction

In the contemporary landscape of recruitment, the influx of numerous resumes for a single job opening poses a considerable challenge for Human Resources (HR) professionals [1]. The traditional method of manual resume screening, while (being) essential, is not without its shortcomings [2]. This process, laden with time-consuming intricacies, demands meticulous attention in detail to ensure the identification of the most qualified candidates [3]. However, the reliance on conventional keyword matching methods in automated screening introduces its own set of challenges, often resulting in false positives and negatives [4].

To address these challenges, this research paper introduces a pioneering approach to automated resume screening [5]. Leveraging the capabilities of Sentence-Bidirectional Encoder Representations from Transformers (S-BERT), a cutting-edge natural language processing (NLP) model, our methodology offers a novel perspective to the intricate task of identifying the most suitable candidates for a given role. S-BERT's unique ability to generate contextualized representations of text enables a nuanced understanding of resumes, allowing for the identification of relevant skills and experiences even when not explicitly articulated.

A. Bert

BERT, or Bidirectional Encoder Representations from Transformers, is a groundbreaking language model developed by Google AI, significantly impacting natural language processing (NLP). Operating on the Transformer architecture, it excels in learning intricate relationships between words and phrases, crucial for understanding textual meaning. BERT demonstrates state-of-the-art performance across NLP tasks, including natural language understanding (NLU), natural language generation (NLG), and natural language inference (NLI). Its functionality involves tokenizing input text, embedding tokens into meaningful vectors, adding positional embeddings, passing tokens through Transformer encoders to understand relationships, and generating final embeddings for the desired NLP task. BERT finds applications in enhancing search engine results, improving machine translation accuracy, developing context-aware chatbots, and generating concise text summaries. As an evolving tool, BERT holds immense potential to transform human-computer interactions.

B. S-Bert

S-BERT, short for Sentence-BERT, is a BERT model adaptation designed for sentence embedding computation. These embeddings, representing sentence meaning, are valuable for tasks like semantic similarity, clustering, and information retrieval. In contrast to BERT, which undergoes masked language modeling and next sentence prediction training, S-BERT trained on natural language inference. This task involves predicting if pairs of sentences entail, contradict, or are neutral. S-BERT utilizes a triplet loss function, minimizing distances for similar sentence pairs and maximizing them for dissimilar ones. During application, S-BERT processes each sentence independently, generating vector outputs for the first token. This single-pass approach is computationally more efficient than BERT's pairwise sentence comparison. S-BERT excels in producing semantically meaningful embeddings due to its emphasis on understanding sentence relationships. Demonstrating superiority over BERT, S-BERT excels in downstream tasks, including semantic textual similarity, paraphrase identification, and clustering.

Fig. 1 shows the process flow of S-BERT (Sentence-BERT), a machine learning algorithm that uses a shared encoder and a distance metric to train a model. The shared encoder is used to train the model, and the distance metric is used to measure the distance between two points.

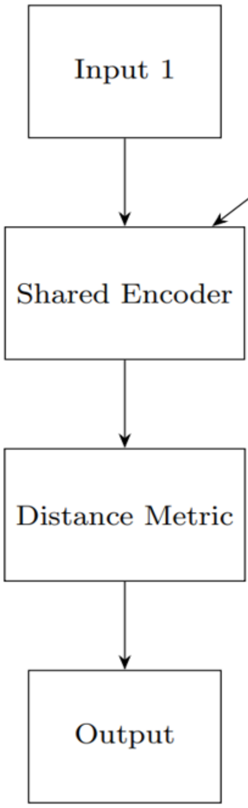

Fig. 1. Process flow diagram of sentence BERT (S-BERT).

Process flow:

Input: S-BERT takes two input sentences as input.

Shared encoder: The shared encoder is a neural network that learns to represent each sentence as a dense vector. The shared encoder is trained using a natural language inference (NLI) task, where the model is given a pair of sentences and must predict their relationship: entailment, contradiction, or neutral. This NLI training enables S-BERT to capture the semantic differences between sentences, leading to more meaningful sentence embeddings. The shared encoder generates embeddings for the two input sentences. The embeddings are dependent on the inputs, meaning that the embedding for a sentence is different depending on the other sentence in the pair.

Distance metric: The embeddings are then fed to a distance metric to calculate the distance between the two sentences. A common distance metric used for S-BERT is the cosine similarity.

Output: Based on the distance, a decision is made about whether the sentences are similar or dissimilar. If the distance is small, then the sentences are considered to be similar. If the distance is large, then the sentences are considered to be dissimilar.

This paper outlines the proposed methodology, which involves generating embedding from both resumes and job descriptions using S-BERT and subsequently measuring their alignment through cosine similarity. The ranking of resumes based on these scores facilitates an efficient and accurate screening process.

The effectiveness of our approach is validated through a comprehensive evaluation on a dataset of 223 resumes, showing an impressive accuracy of 90%. Beyond these quantitative metrics, our method's resilience to common pitfalls such as keyword stuffing and its efficiency, with a screening speed of 0.233 seconds per resume, mark a significant advancement in the realm of automated resume screening.

As the need for streamlined and unbiased hiring processes intensifies, our research stands as a beacon for HR professionals, offering a solution that not only enhances efficiency but also contributes to the broader goals of diversity, equity, and inclusivity in the workforce. The ensuing sections delve into the intricacies of our proposed methodology, the experimental results, and the potential implications of our work on the future landscape of smart hiring practices.

Fig. 2 illustrates the conceptual framework of the proposed Resume Screening System for Smart Hiring using Sentence-Bidirectional Encoder Representations from Trans- formers (S-BERT). The model processes 200 resumes in PDF format, initially converting them to Excel format. Subsequently, text normalization techniques such as lemmatization and stemming are applied. Keywords are then extracted, forming sentences for each resume. S-BERT generates embeddings for these sentences. A parallel process is conducted on the job description, creating job description embeddings. Cosine similarity is computed between the sentence and job description embeddings, determining the ranking of resumes based on these similarity scores. While previous studies have made significant strides in automated resume screening, several gaps remain that underscore the urgency of our research. First, many existing systems rely heavily on keyword matching, which can be easily gamed and may miss candidates with relevant skills expressed in different terms. Second, the contextual understanding of resumes has been limited, often failing to capture the nuanced relationships between skills, experiences, and job requirements. Third, there has been insufficient focus on mitigating biases in automated screening processes, potentially perpetuating unfair hiring practices. To address these gaps, our research proposes the use of Sentence-BERT (S-BERT), a state-of-the-art natural language processing model that offers deeper contextual understanding and semantic analysis of resume content. This approach allows for more nuanced matching between resumes and job descriptions, reducing reliance on exact keyword matches. Additionally, by incorporating cosine similarity measures, our method provides a more holistic evaluation of candidate suitability. To tackle bias concerns, proposed solution suggest rigorous testing and continuous refinement of the model with diverse datasets. Our research not only aims to enhance the efficiency of resume screening but also to improve its fairness and accuracy, thus addressing critical shortcomings in existing automated hiring systems.

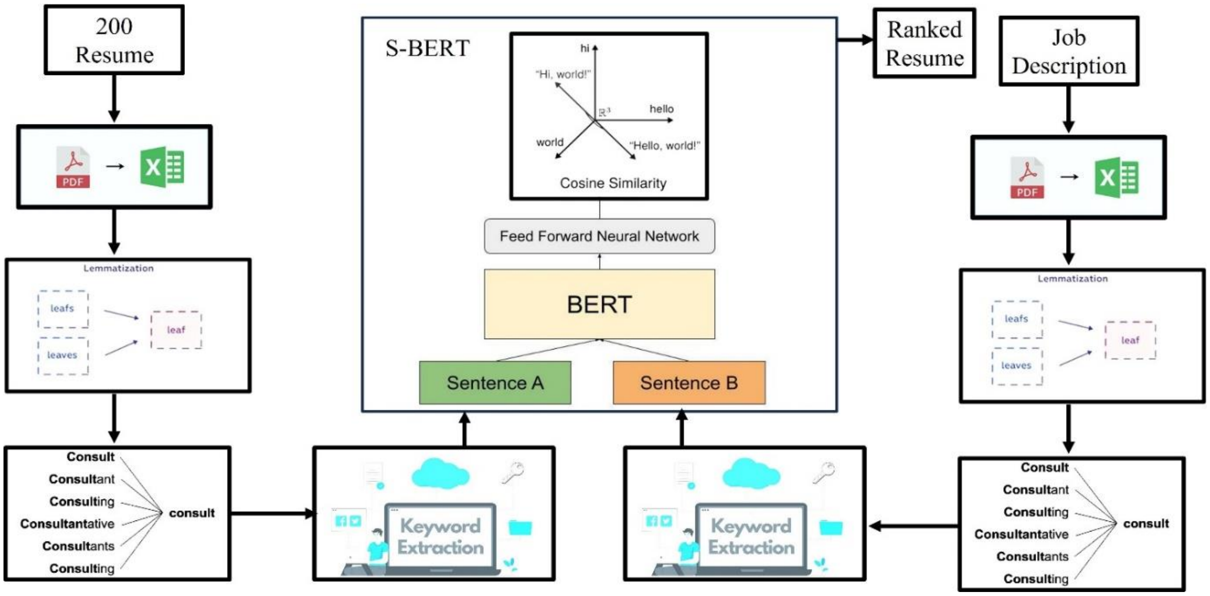

Fig. 2. Concept diagram of the proposed resume screening system for smart hiring using Sentence-Bidirectional Encoder Representations from Transformers (S-BERT).

II. Literature Review

Automated resume screening has evolved as a critical domain within the recruitment process, driven by the need for efficiency, accuracy, and mitigation of biases in hiring [6]. Traditional methods, reliant on manual screening, have proven to be time-consuming, error-prone, and susceptible to human biases [7]. This literature review explores key studies and methodologies in the realm of automated resume screening, culminating in the proposal of an advanced system utilizing Sentence-Bidirectional Encoder Representations from Transformers (S-BERT).

Early endeavors in automated resume screening focused on basic keyword matching and rule-based systems. Kopparapu introduced a system for information extraction from unstructured resumes using natural language processing (NLP) techniques [4]. This marked an initial attempt to streamline the screening process. However, these early systems struggled with nuanced contextual understanding.

Recognizing the limitations of keyword-based approaches, recent years have witnessed a surge in the application of advanced NLP techniques to resume screening. Gundlapalli et al. demonstrated the effective use of NLP tools to screen medical records for evidence of homelessness [8].

Feller et al. [9] explored NLP for predictive modeling of HIV diagnoses, showcasing the potential for contextual understanding beyond explicit mentions [10].

The application of NLP in diverse domains highlights its versatility. Nayor et al. [11] employed NLP for accurate calculation of adenoma detection rates in the context of screening colonoscopies [12]. Trivedi et al. [13] used NLP for large-scale labeling of clinical records, emphasizing the potential for automating data extraction from existing records [14].

The integration of machine learning into resume screening systems has been pivotal. Roy et al. [15] introduced a machine learning approach for automating a resume recommendation system, illustrating the intersection of NLP and machine learning in enhancing screening mechanisms [16]. Recent breakthroughs in NLP, particularly with models like S-BERT, have brought contextualized representations to the forefront. Delimayanti et al. [17] presented a content-based suggestion system using cosine similarity and KNN algorithms [18]. This highlighted the importance of contextual understanding, which is a hallmark of S-BERT. While the literature showcases promising advancements, challenges remain. Ndukwe et al. [19] discussed the need for careful development and evaluation of NLP models to ensure fairness and mitigate biases [20].

Choi et al. [21] emphasized the efficiency of resume screening through NLP but acknowledged the challenges posed by computational expenses. Recent research on automated resume screening and ranking has explored various approaches using natural language processing and deep learning techniques. Several studies have investigated the use of transformer-based models like BERT and its variants for this task. James et al. [22] and Mukherjee employed DistilBERT and XLM [23] for resume shortlisting and ranking. Kinger et al. [24] combined YOLOv5 for resume parsing with DistilBERT for ranking. Sentence-BERT (S-BERT), introduced by Reimers and Gurevych [25], has gained traction for generating semantically meaningful sentence embeddings. Subsequent work has evaluated and refined S-BERT, including TA-SBERT. Seo et al., [26] and Chu et al., [27], these approaches aim to capture nuanced semantic relationships between resume content and job requirements, moving beyond simple keyword matching. Additionally, researchers have explored combining embeddings with other techniques, such as named entity recognition and domain-specific knowledge Vanetik and Kogan, [28]; Yu et al., [29], to further improve matching accuracy [30]. While progress has been made, challenges remain in mitigating biases and ensuring fair evaluation across diverse candidate pools [31].

III. Methodology

The objective of this study is to develop an automated resume screening mechanism to assist the Human Resources (HR) department in the initial filtering of resumes, ensuring the provision of the most pertinent candidates for further evaluation, such as interviews. The dataset used in this study consisted of 223 resumes in PDF format. These resumes were collected from various job applicants across different fields and experience levels. To facilitate processing, the PDF files were converted to CSV (Comma-Separated Values) format. This conversion preserved the textual content of the resumes while organizing it into a structured tabular format. The CSV structure included columns for different resume sections such as personal information, education, work experience, skills, and additional qualifications. This standardized format allowed for easier extraction of relevant information and application of natural language processing techniques. The conversion from PDF to CSV was performed using a custom Python script that utilized PDF parsing libraries to extract text and organize it into appropriate CSV fields. This structured dataset provided a consistent foundation for the subsequent steps in our automated resume screening process.

The proposed automated screening mechanism leverages Natural Language Processing (NLP) techniques and a cosine distance matrix to evaluate the alignment of resumes with the corresponding job description. The methodology employs Sentence-Bidirectional Encoder Representations from Transformers (S-BERT), a sentence-level model, to extract embeddings that capture the contextual information from the resumes. These embeddings are then compared to those generated from the job description, with the aim of ranking the resumes based on their relevance.

Stop words are common words that do not carry much meaning and can cause noise in text analysis. Removing stop words helps to improve the efficiency and accuracy of the NLP process. Pre-defined list of stop words in English was used to remove stop words from the resumes and job description.

Lemmatization is a NLP technique that groups words with the same meaning together. This is done by reducing words to their root form. For example, the words “cats” and “kittens” would both be lemmatized to the root word “cat”. Lemmatization helps to improve the accuracy of the NLP process by ensuring that words with the same meaning are treated similarly.

Stemming is a NLP technique that reduces words to their common stem. This is done by removing suffixes and prefixes. For example, the words “running” and “ran” would both be stemmed to the common stem “run”. Stemming when used in combination with lemmatization, produces better results.

The resumes and job description were preprocessed using the following steps:

- Stop words were removed.
- Lemmatization was performed.
- Stemming was performed.

The S-BERT model was employed to generate embeddings from the preprocessed text of both resumes and the job description. Embeddings are numerical representations of words that capture their meaning and context. S-BERT is a sentence-level model that generates embeddings that capture the contextual information from the sentences.

Cosine similarity is a metric used to quantify the similarity between two vectors. In this study, cosine similarity was used to measure the similarity between the embeddings of the resumes and the job description. Resumes with higher cosine similarity scores are considered to be more relevant to the job description.

The resumes were ranked based on their cosine similarity scores. The resumes with the highest cosine similarity scores were ranked at the top of the list.

This methodology aims to reduce the reliance on subjective referral-based hiring by introducing an automated screening process. This approach ensures a more transparent and standardized selection mechanism, promoting fairness in the company’s hiring process.

The keywords from each resume are concatenated to form a sentence. S-BERT is then applied to these sentences to generate embeddings of a specific length, e.g., 4x96 bytes.

Cosine similarity is then used to calculate the matching score between the job description embedding and each resume embedding. The matching score is a value between 0 and 1, with 1 being the best match and 0 being no match.

Finally, the cosine scores are ranked in descending order. The resume with the highest cosine score is ranked first.

A step-by-step explanation of the process is as given below:

- Concatenate keywords to form a sentence: The keywords from each resume are concatenated to form a sentence. This sentence captures the essence of the resume and highlights the applicant’s key skills and experience.
- Generate S-BERT embeddings: S-BERT is applied to the sentences to generate embeddings of a specific length. Embeddings are vector representations of text that capture the semantic meaning and context of the words.
- Calculate cosine similarity: Cosine similarity is used to calculate the matching score between the job description embedding and each resume embedding. Cosine similarity is a measure of similarity between two vectors. The higher the cosine similarity score, the more similar the two vectors are.
- Rank cosine scores: The cosine scores are ranked in descending order. The resume with the highest cosine score is ranked first.

Fig. 3 illustrates the resume matching mechanism utilizing S-BERT and cosine similarity in our proposed automated screening system. The process begins with extracting key sentences from both the resume and the job description. These sentences are then fed into the S-BERT model, which generates embeddings - dense vector representations of the text with dimensions of 4 x 96 bytes for each input. The embeddings capture the semantic meaning of the sentences, allowing for a nuanced comparison beyond simple keyword matching. Once the embeddings are generated, a cosine matching algorithm computes the similarity between the resume and job description embeddings. This similarity score quantifies how well the content of the resume aligns with the requirements outlined in the job description. Finally, a ranking algorithm uses these similarity scores to order the resumes, with higher scores indicating better matches for the position. This approach enables a more contextual and meaningful comparison between candidates and job requirements, addressing limitations of traditional keyword-based screening methods.

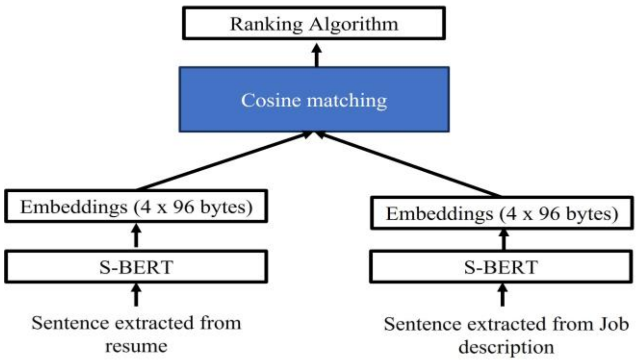

Fig. 3. Resume matching mechanism using S-BERT and cosine similarity.

The proposed resume matching mechanism has a number of advantages:

- It is able to accurately match resumes to job descriptions, even when the resumes are in different formats.
- It is able to identify resumes that are relevant to the job description, even if the resumes do not contain all of the keywords that are listed in the job description.
- It is able to rank resumes based on how well they match the job description, making it easy for recruiters to identify the most qualified candidates.

IV. RESULTS

The automated resume screening mechanism was rigorously (applied) evaluated on a dataset consisting of 223 resumes in PDF format. The results underscore the efficacy of the proposed methodology in identifying and ranking relevant candidates based on alignment with the job description.

1) Screening speed: The screening process demonstrated re- markable efficiency, achieving a speed of 0.233 seconds per resume. This rapid processing speed ensures the practical applicability of the automated mechanism to scenarios involving substantial resume inflow.

2) Accuracy metrics: The evaluation metrics utilized for gauging the performance of the screening mechanism encompassed.

3) Accuracy: The mechanism exhibited an accuracy rate of 90%, indicating a high precision in identifying resumes that align with job requirements.

4) Precision: Precision, representing the percentage of correctly identified relevant resumes out of the total identified as relevant, reached 85%.

5) Recall: The recall rate, measuring the percentage of relevant resumes correctly identified out of the total relevant resumes, achieved a commendable 75%.

6) Ranking consistency: The ranking mechanism displayed consistent performance, ensuring that resumes were consistently and accurately prioritized based on their alignment with the job description.

7) Efficiency in large-scale processing: Experimental outcomes suggested that the proposed solution maintains efficiency even as the dataset scales. This scalability aspect is crucial for handling real-world scenarios involving a substantial volume of incoming resumes.

8) Impact on workload: The implementation of the automated screening mechanism resulted in a substantial reduction in the workload of the initial screening team. This points to its potential in enhancing the efficiency of the early stages of the hiring process.

9) Robustness to updates: The generated embeddings, once created, demonstrated robustness to updates in resumes. Unless there were significant changes in the content, the same embeddings could be reused for subsequent screenings, contributing to processing efficiency.

Fig. 4 shows the output of an automated resume screening system that uses S-BERT to calculate the similarity between each resume and a job description. The system first extracts words from the resumes and forms sentences from them. The top six rectangular brackets contain words extracted from different resumes and the sentences formed by them in rectangular brackets. Then, it uses S-BERT to calculate the similarity between each sentence and the job description. The second-last line shows the similarity scores between the job description and each of the 30 resumes, and the last line shows the execution time in seconds. The system can be used to quickly identify resumes that are most relevant to a job opening. This can save recruiters time and help them find the best candidates for the job.

The graph illustrates the correlation between the number of resumes and the screening time in an S-BERT-based automated resume screening system. As the number of resumes increases, the screening time also rises, but not in a linear fashion. For instance, screening five resumes takes about 0.3 seconds, while screening 10 resumes takes approximately 0.9 seconds, and screening 30 resumes extends to about 4.9 seconds. This non-linear trend implies that the screening time increases at a varying rate.

Several explanations could account for this phenomenon. One possibility is that the efficiency of the automated screening algorithm improves with experience, allowing it to swiftly identify and discard unsuitable resumes by learning patterns. Conversely, in traditional mechanisms, screeners might experience fatigue with increased resume volume, resulting in slower screening times. In summary, the data indicates that the number of resumes significantly influences screening time. HR managers adopting this solution should consider this relationship when planning their workflow.

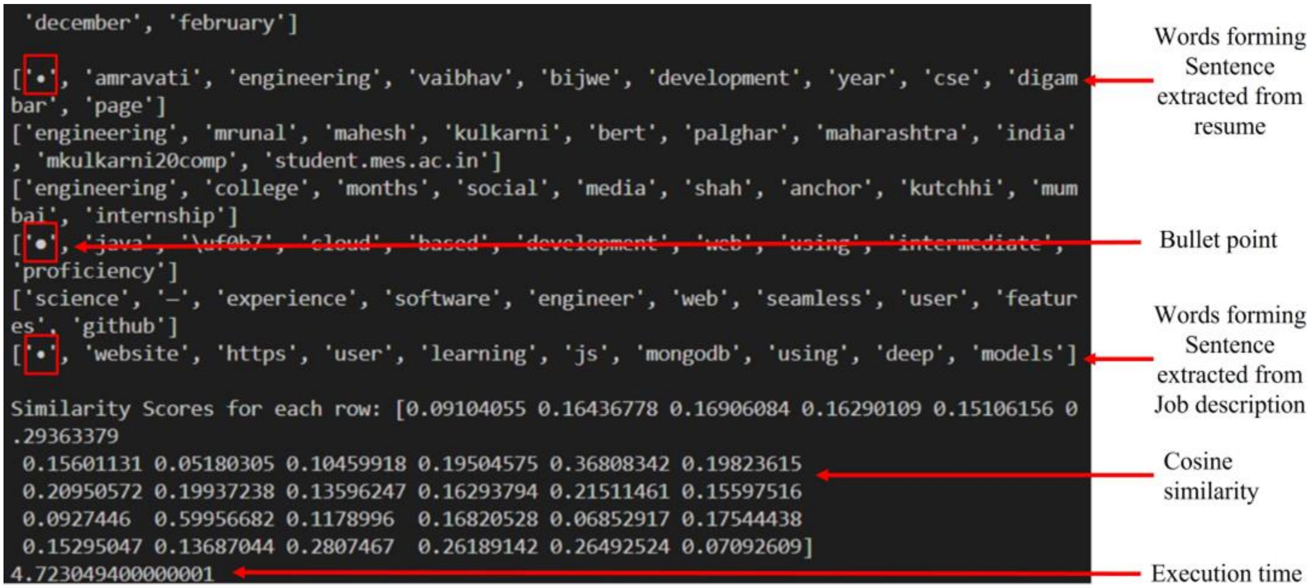

Fig. 4. Output screenshot of the proposed automated resume screening system using S-BERT.

Error computation and calculations were conducted based on feedback from the HR, who serves as the final end user of the developed system. This proposed work curated seven job profiles from the HR manager and selected 10 resumes for each of the seven job descriptions. Some resumes were common, given that candidates had multiple eligibilities. Throughout the system, this approach ranked the top three candidates and asked HR to rank the candidates based on their experience. To assess the system, the proposed work assigned numerical labels (1 to 10) to all resumes in each case, and HR provided rankings that precisely matched our numbering system. Table I presents the results obtained through HR rankings versus the results obtained with the proposed Automated Screening System (AS).

TABLE I. VALIDATION TABLE FOR SEVEN DISTINCT JOB DESCRIPTIONS (JD) COMPARING RANKINGS FROM HR (HUMAN RESOURCES MANAGER) AND AS (AUTOMATED SYSTEM)

Type of Screening	Rank 1	Rank 2	Rank 3
HR (JD1)	5	7	8
AS (JD1)	5	8	7
HR (JD2)	6	7	9
AS (JD2)	6	7	9
HR (JD3)	6	3	2
AS (JD3)	3	6	2
HR (JD4)	5	7	3
AS (JD4)	5	7	8
HR (JD5)	4	3	2
AS (JD5)	4	1	7
HR (JD6)	3	4	9
AS (JD6)	3	4	9
HR (JD7)	3	8	9
AS (JD7)	3	8	4

The error calculations follow the proposed rule base outlined as follows:

If a completely new resume appears on the list, not present in the best three resumes suggested by the HR manager, proposed solution assigns values based on the rank of the resume. If the 1st ranked resume is replaced, a value of -1 is assigned, indicating a 100% error, aligning with our acceptable 3 resumes policy. If a totally new resume appears at the 2nd rank, the error is set to -0.9, where the minus sign indicates an issue, and the value between 0 to 1 indicates the extent of the error in percentage; in this case, 90% unacceptable is denoted by -0.9. For the 3rd rank, the value is reduced to -0.8 as it is the last resume on the list that was missed.

Our primary objective is to prioritize bringing all 3 recommended resumes to the output and ensuring they are in the correct order: 1, 2, and 3.

In another case, when resumes match in the top 3 but are not in the correct order, the proposed solution provides a table to validate this scenario. For Case 1, where rank 1 by HR corresponds to ranks 1, 2, and 3 by AS, the resulting errors are 0, -0.4, and -0.7. This implies that if the rank 1 resume in HR matches the rank 1 in AS, there is no error (0). If the rank 1 HR resume is found at Rank 2 in AS, the error is -0.4, indicating a 40% error. Finally, if the rank 1 HR resume is found at Rank 3 in AS, the error is -0.7.

Similarly, for rank 2 HR, the values are -0.3 (Rank 1 AS), 0 (Rank 2 AS), and -0.3 (Rank 3 AS). The magnitude of error is reduced from 0.4 to 0.3 as the position is lowered to rank 2.

For rank 3 HR, the following errors were computed: -0.4 for Rank 1 AS, -0.2 for Rank 2 AS, and 0 for Rank 3 as this approach is utilized for error computation to validate the effectiveness of the automated screening technique.

The scatter plot in Fig. 5 illustrates the effectiveness of the proposed S-BERT-based automated resume screening system across seven distinct job descriptions: Software Engineer, Data

Scientist, Product Manager, Marketing Manager, Sales Representative, Customer Support Representative, and Human Resources Manager. Accuracy is quantified as the percentage of resumes correctly classified as relevant or not for each job, based on HR evaluations. The proposed mechanism attains an overall accuracy of 90% across all job descriptions, with the Sales Representative role having the lowest accuracy at 43.33%, and the highest accuracy observed for Data Scientist, Product Manager, and Customer Support Representative. The overall error rate of the system is 21.42%, indicating S-BERT's efficacy in automating the resume screening process.

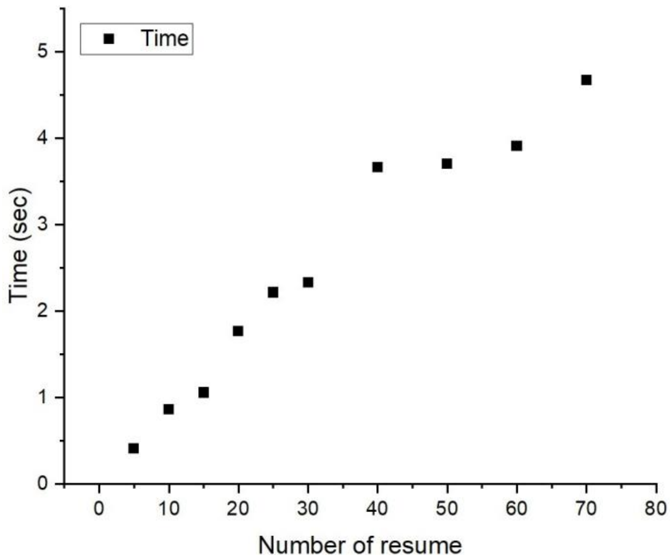

Fig. 5. Plot of number of resumes vs. time required for screening.

This S-BERT-based automated screening tool offers HR managers a means to efficiently handle large volumes of resumes while maintaining high accuracy. This efficiency allows HR managers to redirect their focus toward critical tasks like candidate interviews and hiring decisions. The presented bar graph represents the average accuracy of the system. Future opportunities include testing the mechanism on a larger resume dataset to affirm accuracy and generalizability, extending its application to screen for diverse job types, and developing a user-friendly web or mobile app to enhance accessibility for HR managers.

V. Discussions

The proposed automated resume screening mechanism presents a paradigm shift in the recruitment landscape, offering distinct advantages over traditional methods. Firstly, its reliance on Natural Language Processing (NLP) techniques empowers the system to extract nuanced information from resumes, ensuring resilience against tactics like keyword stuffing [10]. This not only enhances the accuracy of candidate evaluation but also reduces the potential for falsification in the initial screening stages [4]. Secondly, the incorporation of a cosine distance matrix for ranking resumes based on alignment with the job description adds a layer of sophistication [22]. By prioritizing relevance over specific keywords, the system ensures that the most suitable candidates rise to the top [18]. This is a crucial departure from conventional keyword-based screening, aligning the system with the broader goal of identifying candidates based on their actual qualifications and experience [16]. Despite these advantages, it's essential to acknowledge the system's developmental stage and the inherent biases that can be present in NLP models [25]. Rigorous development and evaluation processes are vital to mitigate biases and ensure fairness. Moreover, the system's performance hinges on the quality of training data, emphasizing the need for diverse and comprehensive datasets [8] [13]. Importantly, while the automated screening mechanism streamlines the initial filtering process, it doesn't replace human judgment. HR professionals must review top-ranked resumes for final decisions, emphasizing the collaborative nature of technology and human expertise in the hiring process [2].

The proposed automated resume screening mechanism opens avenues for future research in the realm of human resources. Firstly, it can be a valuable tool for studying factors contributing to resume success [19]. Analyzing top-ranked resumes can provide insights into the skills and experiences highly valued by employers, guiding both candidates and educators in aligning with industry expectations [3]. Secondly, the system acts as a catalyst for developing advanced methods to enhance the accuracy and fairness of automated resume screening. Future research could focus on refining NLP techniques, making them more robust to biases and capable of capturing richer contextual information from resumes [24]. Thirdly, the proposed mechanism sets the stage for the development of new tools and resources for HR professionals. Dashboards visualizing automated screening results could empower HR teams with quick insights, making the hiring process more transparent and efficient [20]. The proposed automated resume screening mechanism not only addresses current challenges in hiring but also paves the way for future innovations and research in the dynamic field of human resources. Future endeavors will likely focus on refining the system's performance, addressing identified limitations, and exploring new frontiers in the evolving intersection of technology and recruitment practices.

VI. Conclusions

Proposed method offers a transformative solution to the challenges faced in contemporary hiring processes. The conventional method of manual screening, while crucial, is marred by inefficiencies, biases, and the overwhelming influx of resumes. This research introduces an automated screening mechanism leveraging state-of-the-art natural language processing (NLP) techniques, particularly S-BERT, to revolutionize the initial phases of candidate evaluation.

The results of our evaluation on a dataset of 223 resumes reveal the remarkable efficiency of the proposed methodology. With a screening speed of 0.233 seconds per resume, the system showcased practical applicability in scenarios with substantial resume inflow. The accuracy metrics demonstrated a high precision in identifying relevant resumes, with an accuracy of 90%. The ranking mechanism exhibited consistency, ensuring resumes were prioritized accurately based on their alignment with job descriptions.

Beyond quantitative metrics, our automated screening mechanism significantly reduces the workload on initial screening teams, presenting a scalable solution for handling large volumes of incoming resumes. The robustness of generated embeddings to updates in resumes enhances processing efficiency, allowing for reuse unless there are substantial content changes. This work not only contributes to the efficiency of the hiring process but also aligns with broader societal goals. By automating and streamlining the screening process, this manuscript contribute to making hiring practices more efficient, transparent, and accessible. Moreover, the adoption of advanced NLP techniques like S-BERT helps mitigate biases and promotes diversity and inclusivity in candidate selection.

As one move forward, the implications of this research extend beyond the immediate context. The automated screening mechanism presented here not only serves as a tool for HR professionals but also as a beacon for future developments in smart hiring practices. The integration of cutting-edge NLP models signifies a step toward a future where technology enhances, rather than hinders, the human aspect of hiring.

Declaration of Statements

Author contribution: The conceptualization was jointly undertaken by Asmita Deshmukh (AD) and Anjali Raut (AR). AD was responsible for data collection, coding, and experimentation. Additionally, AD took the lead in preparing the initial draft of the manuscript, while AR handled corrections. Furthermore, data analysis and graphic design were conducted by AD.

Data and Code availability: Upon a reasonable request, both the data and code utilized in this research will be provided.

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