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Deep Semantic Matching for Intelligent Resume Screening Using Hybrid Transformer Architectures

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***Abstract-** With the fast growth of digital recruitment sources, the quantity of employment applications has grown to an all-time high, and screening resumes manually is no longer efficient and effective. The traditional automated screening tools mostly use the method of matching keywords, which does not achieve the semantic background, transferable competencies, and subtle match between applicant profile and the job requirements. To overcome these shortcomings, this paper suggests a smart resume screening system on the deep semantic matching on the basis of hybrid transformer frameworks. The proposed solution involves transformer encoders (specialized to resume and job description) along with cross-attention and feature fusion to predict fine-grained contextual relation. The system can score relevance accurately across beyond the surface-level similarity of text and therefore project both documents into common semantic embedding space. Further semantic skill normalization and experience-sensitive weighting enhance the robustness of the skills in a wide range of resume forms and domains. The experimental analysis based on publicly available data proves that the suggested framework is more accurate and more effective in ranking compared to key-powered and single-transformer baselines. The findings underscore the scalability and interpretation and next-generation recruitment systems possibilities of the framework.*

***Keywords:** Intelligent Resume Screening, Deep Semantic Matching, Hybrid Transformer Architecture, Resume–Job Matching, Natural Language Processing*

I. INTRODUCTION

The rising trend of using online recruitment tools has radically changed the way the hiring process takes place because it allows companies to tap into a worldwide talent pool. Though the expansion has the advantage of improving reach and diversity, it has brought about a major challenge where the high volume of resumes has to be screened in a timely and objective fashion [1]. Manual screening of resumes is not only time-consuming and inaccurate, but also prone to human error, particularly when a recruiter has thousands of resumes per job vacancy. Consequently, automated resume screening systems are a new vital aspect of the modern recruiting processes [2].

First automated screening systems were mostly based on shortlisting candidates by search using keywords and rule-based filters [3]. Even though they are computationally efficient, they experience poor semantic comprehension and do not identify contextual relevance, transferable skills, and varied terminologies applied in resumes. As an example, applicants since they have similar competencies might share their experience in different words thus causing wrongful instructions. In addition, strict keyword matching ignores unspoken requirements, cross-disciplinary skills and career advancement, and, thus, compromises effectiveness in the general success of such a hire [4].

The latest developments in Natural Language Processing (NLP), most notably the rise of transformer-based language models, have contributed in a huge way to the contextual representation of text and semantic interpretation. Transformer models are trained on deep linguistic patterns and contextual dependencies and would be suitable in analyzing unstructured resume information. Nonetheless, a straightforward application of one of the transformer models to restart the screening process is incomplete. Resumes and job descriptions are different because of their structure, purpose and density of information needed to be fine-tuned with specific modeling to obtain a fine semantic alignment. Also, current methods are usually not flexible in the domains and do not coordinate the relevancy of skills, experience years, and position-specific demands [5].

In order to resolve these issues, the present research proposes a novel deep semantic matching framework based on the intelligent resume screening via hybrid transformer architectures. The rationale behind the proposed approach is to use contextual language encoders together with job description-specific attention mechanisms to model resumes and job descriptions jointly in a common semantic embedding space. The system presents both semantically rich representation of global meaning and finely-grained relational dependency between candidate qualifications and job requirements by exploiting hybrid transformer representations. This design allows relevant scoring which is not just based on superficial text similarity.

Moreover, the offered system includes semantic normalization of skills and weighted experience modelling to resolve inconsistency in resume format and words. These processes increase robustness in multiple candidate profiles and areas of recruitment, and the matching decisions are easily interpreted. The framework will be scalable and flexible, which makes it adaptable to the real-life recruitment process with constantly changing job specifications. This work has three major contributions. To begin with, it introduces a hybrid transformer-based structure that is semantically resume-job matching. Second, it presents a smart relevance scoring model, which takes into consideration situational aptitude fit and experience richness. Third, it proves through experimental analysis that the suggested approach can be more successful than the classical keyword-based systems and single-model transformer baselines. This research, on the whole, will improve the current state of automated recruitments by offering an intelligent, precise, and context-sensitive resume screening system.

II. LITERATURE REVIEW

Table 1: Summary of Related Work on Resume Screening and Job Matching

Ref.	Methodology	Key Contribution	Limitations
[6]	NLP + Deep Learning ranking framework	Proposes a resume ranking and sorting framework using NLP features and deep learning models for candidate shortlisting	Limited semantic interaction between resumes and job descriptions
[7]	Hybrid Deep Learning + Skill NER	Introduces DeepSkillNER for automatic resume screening and skill-based ranking using hybrid deep learning	Focuses mainly on skill extraction rather than holistic semantic matching
[8]	YOLOv5 + DistilBERT	Combines visual layout detection with semantic text modeling for resume parsing and ranking	High dependency on resume layout and visual features
[9]	Multimodal AI-based web system	Develops a scalable multimodal resume ranking web application for large-scale recruitment	Lacks fine-grained semantic alignment using attention mechanisms
[10]	Transformer-based Ensemble + LIME	Extracts technical and non-technical skills from job descriptions using explainable ensemble models	Does not perform end-to-end resume–job matching
[11]	Unsupervised Embeddings + Contrastive Learning	Proposes ResJobFit, an efficient embedding-based resume–job matching system	Missing explicit cross-attention between resume and job content
[12]	NLP + Jaccard/Cosine Similarity	Automates resume screening by matching extracted competencies with predefined skill sets	Relies on lexical similarity, weak contextual understanding
[13	AI Agent +	Introduces a	Focused on job

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]	NLP	personalized job recommendation and application assistant agent	recommendation, not resume screening accuracy
[14]	SpaCy Transformer BERT + NLP	Proposes a hybrid resume parsing system for structured data extraction	Limited to parsing; no semantic ranking or matching
[15]	Transformer-based Embeddings	Introduces Resume2Vec for embedding-based resume–job matching aligned with human judgment	Lacks token-level interaction and explainable score decomposition

Based on the above studies, it is noted that the available approaches are either resume parsing or skill extraction or embedded based similarity. Nevertheless, there is a lack of work that deals with deep semantic interaction, contextual alignment, and explainable scoring at the same time, and it is this reason that is behind the proposed hybrid transformer-based.

III. PROPOSED METHODOLOGY

The intelligent resume screening system being proposed will conduct deep semantic matching between the candidate resumes and the job descriptions with the help of hybrid transformer-based architecture. The system will address the shortcomings of the conventional keyword-based and single-model NLP methods by incorporating contextual representation learning, domain adaptation, and relevance-aware ranking into one system. The system is applicable to scalable real world recruitment environments because figure-level architectural explanations can be drawn directly on the modular structure that is outlined in this section.
The general scheme of the suggested system will include five key steps, namely data preprocessing and normalization, semantic representation learning, semantic matching with the help of a transformer, relevance scoring and ranking, and explainable output production. The stages are intended to solve a particular issue related to resume screening, such as the heterogeneous document format, the lack of consistency in terminology, and the necessity of the interpretation in decision-making.

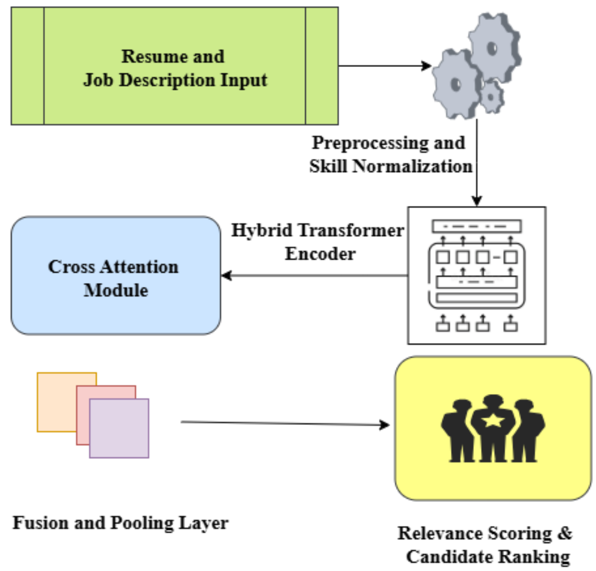

Figure 1: System architecture of the proposed intelligent resume screening framework illustrating preprocessing, hybrid transformer encoding, cross-attention based semantic alignment, and relevance-aware candidate ranking

During the preprocessing phase, resumes, and job descriptions will be received in different formats (PDF, DOCX, plain text and so on). The initial step in these documents is to transform them into a format-independent textual representation by format-neutral parsing. Noise cleanup steps are used to remove unnecessary data like headers, footers, ornamental characters and unnecessary whitespace. Then domain-specific tokenization is carried out to maintain such important information as technical words, certifications and numbered phrases upon experience term. Techniques of named entity recognition are also applied optionally to recognize structured elements like skills, educational qualifications, organizations and job roles and allow downstream semantic normalization.

After preprocessing, semantic normalization is done by the system to eliminate the difference in vocabulary between resumes. A curated skill ontology and contextual similarity analysis are used to map skills and role descriptions to canonical representations. The purpose of this step is to enable the system to identify semantically equivalent skills in cases where they may be formulated using dissimilar terminology, e.g. abbreviations, synonyms, or phraseology of the domain. The information of experience is normalized by the extraction of the temporal expression and weighted values (depending on their relation to the target job role). This will be to make sure that the recent and role-specific experience is more relevant to the matching process than irrelevant or obsolete information.

The essence of the suggested system is represented by the semantic representation learning stage that applies a hybrid transformer version. The framework does not use one pre-trained model, but rather it uses multiple transformer encoders to build on supplementary semantic features. A single encoder of the transformer is optimized around resume information, in particular on the resume data to model candidate-focused information which includes skills development, project summaries and career development. The second encoder is job description adapted to understand job expectations, demanded competencies and circumstances. These encoders produce heavy contextual embeddings that are able to maintain both the syntactic structure and semantic meaning.

A cross-attention mechanism is presented in order to improve the interaction between resume and job description representations. This process enables the model to explicitly learn the association between resume sections and the related job specifications to semantically match these sections finely. To give an example the system is able to match the project-related experience of the candidate that fits in the given job description notwithstanding the fact that they are described in a different linguistic pattern. The hybrid architecture also includes a fusion layer that adds the outputs of the respective encoders and the cross-attention module to form a single semantic representation that is optimized to get matching tasks. After generating the unified embeddings, deep semantic matching is done in a common latent space by the system. Similarity based on cosine and learned relevance operations are used together to compute the alignment score between job description and resume. In contrast to classical measures of similarity, the relevance function suggested is trained in such a way that prioritises the most crucial job needs and gives flexibility to inter-disciplinary experience and transferable skills. A weighted scoring system incorporates the relevance of the skills, the depth of the experience, and the similarity of context, and gives a composite score of relevance to every candidate.

The system will also have the ability to be dynamically weighted according to the priorities of the job to achieve robustness and flexibility. Recruiters can make their priorities specific in terms of the focus on specific professional skills, leadership experience, or education. These preferences are added into the relevance scoring layer without having to retrain the model, and it enjoys a more practical usability. There is also threshold-based filtering which is used to eliminate low-relevance candidates earlier in the ranking process, enhancing computational efficiency in the large-scale recruitment case.

Explainability is also another significant feature of the proposed system, which can be viewed as a solution to the increasing need of the transparent AI-driven decision-making. The framework also has an explanation module which would allow tracking of corresponding scores to resume sections contributing to the score and job specifications. The focus on visualization of weight and feature attribution methods are used to point out what skills, experience, or qualifications were implicated in the final ranking. This does not only enhance the level of trust on the part of the recruiter, but also allows the applicant to get constructive feedback on how well their application fits.

The system suggested is trained and assessed by the help of supervised and weakly supervised learning strategies. The matching model is optimized using labeled datasets of resume jobs pairs with relevance i/o. In conditions of the limited availability of labeled data, the system utilizes contrastive learning methods and pseudo-labeling to enhance generalization. There is regularization and domain adaptation method that is performed to avoid over-fitting and performance uniformity in different industries and job categories.

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On the whole, the offered hybrid transformer-based resume screening solution is a holistic and intelligent approach to automated shortlisting of talents. The framework fuses profound semantic insights, contextual matching, and explicable relevance grading and tackles the major shortcomings of current methods. The system can be scaled, customized to meet requirements, and offer correct and clear candidate ranking, which makes it a good baseline of future generations recruitment technology.

Algorithm

$Input\ \mathcal{R} = \{r_1, r_2, \ldots, r_N\}, j, \mathcal{O}, \Theta = \{\Theta_R, \Theta_J, \Theta_C, \Theta_F, \Theta_S\}, j$

$Output\ \Pi = Ranked\ candidates$

Document Preprocessing

$\forall i \in \{1, \ldots N\}: \tilde{r}_i = \mathcal{P}(r_i), \tilde{j}_i = \mathcal{P}(j)$

Skill and Experience Normalization

$s_i = \mathcal{S}(\tilde{r}_i), s_j = \mathcal{S}(\tilde{j})$

$\hat{s}_i = \mathcal{N}(s_i, \mathcal{O}), \hat{s}_j = \mathcal{N}(s_j, \mathcal{O})$

$e_i = \varepsilon(\hat{r}_i), e_j \varepsilon(j)$

Hybrid Transformer Encoding

$H_i = Enc_R(r_i; \Theta_R) \epsilon \mathbb{R}^{L_i * d}$

$G = Enc_J(\tilde{j}; \Theta_J) \epsilon \mathbb{R}^{L_j * d}$

Cross Attention Alignment

$$A_i = Attn(H_i, G) = softmax\left(\frac{H_i G^T}{\sqrt{d}}\right) G$$

Represented Fusion

$Z_i = Fuse([H_i; A_i]; \Theta_F)$

Global Semantic Pooling

$u_i = Pool(Z_i), v = Pool(G)$

Relevance Components

$\alpha_i = \cos(u_i, v)$

$\beta_i = Sim(\hat{s}_i,, \hat{s}_j)$

$\gamma_i = Match(e_i, e_j)$

$\delta_i = CtxAlign(Z_i, G)$

Final Matching Score

$S_i = \lambda_1 \alpha_i + \lambda_2 \beta_i + \lambda_3 \gamma_i + \lambda_4 \delta_i$

Candidate ranking

$$\Pi = argsort_{i=1}^{N}(S_i, descending)$$

IV. RESULT AND ANALYSIS

The experimental analysis is carried out on the basis of publicly available resume-job matching data made up of anonymous candidate resumes and job descriptions. The information in the dataset is structured and unstructured text, such as skills, summary of experience, education background and job requirements. The association of each resume with each job is accompanied with a relevancy label giving the level of aptitude of a candidate with each job position. A publicly available resume job matching dataset that included resumes and job descriptions of various technical areas was experimented on. A preprocessing process was carried out and the data was divided into training, validation and test sets at a 80:10:10 ratio.

The effectiveness of the suggested hybrid transformer-based resume screening system was tested with the help of a publicly available resume job matching dataset of anonymized resumes and job descriptions of a variety of technical fields. The information contained in the dataset is structured and unstructured in terms of text including skills, experience summaries, educational background and role requirements. Every resume job pair has the relevance label that is used to determine whether a candidate is fit in a specific job position. The dataset was pre-treated and separated into training, validation, and test sets in order to provide an objective evaluation, 80:10:10 split was used. The table 2 provides an overview of the main features of the data set such as the number of resumes, job descriptions, resume-job pair, and the application fields.

Table 2: Dataset Statistics

Attribute	Description
Number of Resumes	1,000
Number of Job Descriptions	100
Resume–Job Pairs	5,000
Labels	Relevant / Not Relevant
Domains	IT, Data Science, Software Engineering

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Language	English

Table 3 shows a quantitative comparison of the proposed hybrid model and two baseline models; a key word-based screening model and a single transformer-based model. The standard classification and ranking measures were applied, i.e. Accuracy, NDCG, Precision at K to evaluate it. As the table demonstrates, the keyword-based screening methodology has a rather low performance level based on all metrics because of the surface-level term matching and the failure to read semantic context. The single transformer model is much better in terms of performance as it exploits contextual embeddings, though it has not achieved fine-grained fit between resumes and job descriptions.

Table 3: Comparison Table (Baseline vs Proposed Method)

Method	Accuracy	NDCG	Precision@K
Keyword-Based Screening	0.68	0.62	0.65
Single Transformer Model	0.81	0.78	0.80
Proposed Hybrid Model	0.89	0.87	0.88

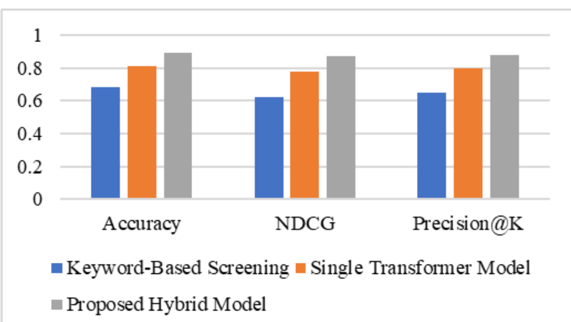

Figure 2: performance Comparison with Baseline Methods

The hybrid transformer proposed is clearly better than the both baselines with an accuracy of 0.89, NDCG of 0.87 and Precision at K of 0.88. This enhancement shows that a combination of resume-specific and job-specific transformer encoders, coupled with cross-attention and feature fusion mechanisms are effective. The NDCG score is higher which implies high quality of ranking as more relevant candidates are ranked higher on the short list. These findings support the assertion that deep semantic matching facilitates more accurate and reliable resume screening as opposed to the traditional and single-model methods.

The performance comparison of the three methods is also represented graphically in Figure 2 in terms of a bar graph. As is evident in the figure, there was a gradual increase in the optimality of the current screening methods, which were based on keywords, through the single transformer model, and lastly, the hybrid solution, in all the evaluation metrics. This tendency points to the advantage of semantic representations and model interaction. The large difference between the proposed model and the baselines is also a mark of how strong and applicable it will be to actual recruitment processes.

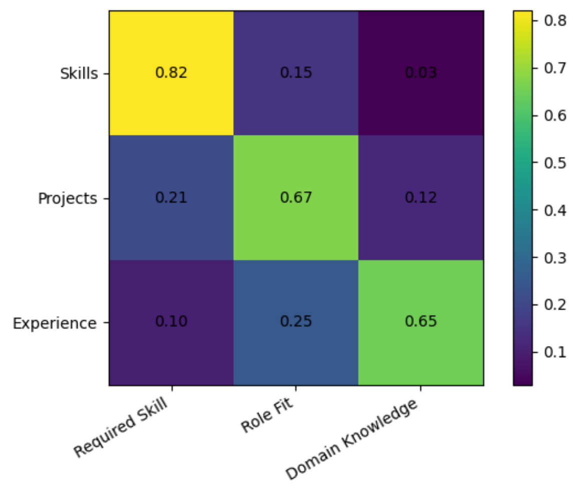

Figure 3: Cross Attention Alignment: Resume job description

Figure 3 shows a visualization of cross-attention alignment between resume and job description requirements. Attention heatmap illustrates that the model concentrates on, and prioritizes semantically relevant resume areas, including skills and project descriptions, in comparison to occupied job requirements in the process of matching the selected requirements to the resume fragments. The weights of attention mean more semantic alignment and it is possible to say that the suggested system is not based on precise overlap of keywords but it follows the contextual relevance. The explainability of the model is supported by this visualization, as well as the effectiveness of the cross-attention mechanism is proven.

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Figure 4 represents the visualization of the semantic embedding space created with the application of t-SNE. In this figure, the resumes and job descriptions are mapped onto a two-dimensional space, in which the more relevant resumes have higher scores in the relevance scale. This tendency of clustering represents the fact that the proposed system is effective to learn a shared semantic embedding space where the relevant candidates tend to be clustered around the target job representation. The visualization is intuitive confirmation of the semantic matching ability of the model and supplements the quantitative results of the evaluation.

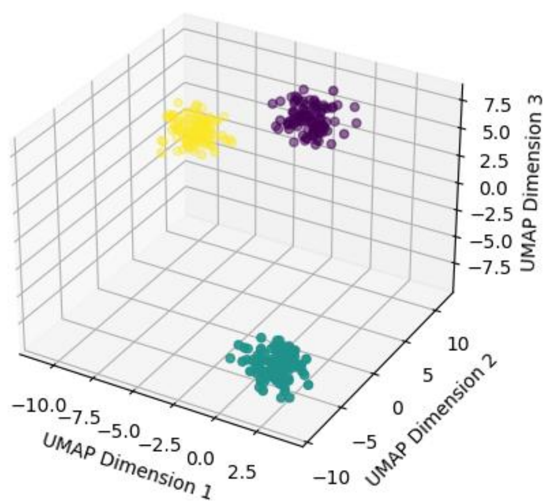

Figure 4: Semantic Embedding space visualization (TSNE)

The match score of resume and job in Figure 5 is presented in a stacked bar chart. The bars depict the individual candidates and the segments used in the stack illustrate the assistance provided by semantic similarity, skill correspondence, experience correspondence as well as the contextual relevance to the overall matching score. This value shows that the contribution of various factors to candidate ranking is interdependent and that the scoring mechanism proposed is interpretable. The system allows the recruiters to appreciate and have faith in the automated decision-making process by breaking down the final score into valuable components.

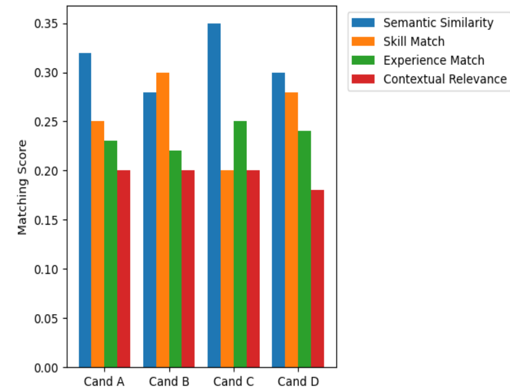

Figure 5: Resume Job matching score breakdown

Altogether, the experimental findings show that the suggested hybrid transformer-based framework has better performance in the resume screening and ranking priorities of the candidates. The quantitative metrics combined with the comparative analysis and visual explanations prove that the deep semantic matching is a lot more effective in terms of accuracy, ranking and transparency. The results confirm the suggested methodology as a scalable and intelligent solution towards the next generation recruitment systems.

V. CONCLUSION

The paper proposed a comprehensive semantic matching system of smart resume screening through hybrid transformer systems. The proposed system achieves this by combining resume-based and job-based transformer encoders with cross-attention and feature fusion to achieve the goal of capturing contextual relations between qualifications of the candidate and job requirements. Experimental findings on an open dataset show that the suggested use case is much more effective at Accuracy, NDCG, and Precision at K than the use of a single-transformer baseline, as well as Keyword-based screening and Visual encodings, the proposed system can interpret semantics, provide effective rankings, and offer explainability. These findings prove the appropriateness of the suggested framework to scalable and transparent automation of recruitment.

Future research will be aimed at expanding the framework to multilingual resume and cross-domain hiring cases. Fairness-based learning and bias reduction methods will also be incorporated in order to improve ethical decision-making. Also, incorporation of big language model to interpret job requirements in an adaptive hiring process and hiring feedback can improve system flexibility and personalization

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