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A Deep Learning Framework for Detecting Fraudulent Online Job Postings

[1]Dr.B.Praveen

Assistant Professor, Department of Computer Science and Engineering, Marri Laxman Reddy Institute Of Technology and Management, Hyderabad

Email id: praveen071205@gmail.com

Abstract: Online recruitment platforms have become a primary medium for job searches, but the increasing volume of fraudulent job postings poses serious risks to job seekers, including identity theft, financial loss, and data exploitation. Traditional rule-based and machine learning methods often fail to detect sophisticated or newly emerging fraud patterns due to the dynamic nature of online scams. This study presents a Deep Learning Framework for Detecting Fraudulent Online Job Postings, designed to automatically learn complex linguistic, semantic, and behavioral patterns associated with recruitment fraud. The proposed system integrates advanced neural architectures—including Bidirectional LSTM, CNN-based text feature extractors, and attention mechanisms—to capture subtle anomalies in job descriptions, employer metadata, and posting behaviors. A large, preprocessed dataset of legitimate and fraudulent job postings is used to train and evaluate the framework. Experimental results demonstrate that the deep learning–based model significantly outperforms traditional machine learning baselines in terms of accuracy, precision, recall, and F1-score, achieving robust detection of deceptive content. This framework contributes an intelligent, scalable, and automated solution, enhancing the safety and trustworthiness of online recruitment platforms while reducing the risk of applicant exploitation.

Keywords: LSTM, architectures, sophisticated, exploitation.

I. INTRODUCTION

The rapid expansion of online recruitment platforms has created unprecedented convenience for employers and job seekers, but it has also given rise to a parallel increase in fraudulent job postings that exploit applicants for financial gain, identity theft, or data harvesting. These deceptive postings erode trust in job marketplaces, impose financial and psychological harm on victims, and complicate moderation at scale for platform operators [1], [2].

Automated detection of fraudulent job ads is challenging because scammers continually adapt wording and tactics, and fraudulent samples are typically a small, long-tailed minority of posted listings. Traditional rule-based filters and classical machine learning classifiers (e.g., SVM, Random Forest) can catch simple scams but struggle with the semantic subtleties and syntactic variations seen in sophisticated frauds. Recent studies emphasize that robust solutions must combine deep language understanding with behavioral and metadata signals to detect evolving scam patterns reliably. [3]–[6].

Deep learning—especially transformer-based language models (BERT, RoBERTa) and hybrid CNN/RNN text encoders—has demonstrated strong results on related tasks such as spam detection, fake news classification, and phishing detection. Several recent works apply NLP and deep learning to fake-job detection, using textual features (title, description, requirements), employer metadata, and posting behavior to learn discriminative patterns that generalize across platforms [7]–[10]. Despite encouraging performance gains, the literature also reports persistent issues: dataset imbalance, limited cross-platform generalization, and the need for explainability when models flag legitimate employers as suspicious.

A number of curated datasets and community projects (e.g., the Kaggle “Real or Fake Job Postings” dataset) have enabled benchmarking and replication, yet dataset heterogeneity and label noise remain obstacles for

reproducible comparison. Moreover, practical systems must combine text models with lightweight feature engineering (e.g., contact email patterns, salary anomalies, remote/telecommute flags) and consider imbalance-aware training (SMOTE, focal loss) or synthetic augmentation to improve recall on scarce fraudulent examples [11]–[14].

Motivated by these observations, this paper proposes a comprehensive deep learning framework that fuses transformer-based textual encoders, convolutional text feature extractors, and engineered metadata features within an imbalance-aware training pipeline. Our framework emphasizes (1) robust semantic understanding of job descriptions, (2) integration of employer and posting metadata, (3) strategies for handling class imbalance and label noise, and (4) deployability considerations for production job platforms. We evaluate the approach on public and aggregated datasets and demonstrate improvements in precision, recall, and F1 over baseline ML and deep learning models while discussing explainability and operational integration [15].

II. LITERATURE REVIEW

Research on detecting fraudulent online job postings has progressed from simple rule-based heuristics to sophisticated deep learning and multimodal models. Kumar et al. [16] provided one of the earliest systematic studies comparing keyword-based rules, feature-engineering pipelines, and classical machine learning classifiers (SVM, Random Forest) on public job-posting datasets, showing that while rule systems are fast, they fail to generalize to adversarially crafted scam posts. Sharma and Rao [17] extended this work by demonstrating that syntactic and lexical cues alone are insufficient and advocated for semantic modelling of descriptions with distributed representations.

The introduction of community datasets and shared benchmarks spurred rapid progress. Singh et al. [18] analyzed the widely used Kaggle “Real or Fake Job Postings” dataset and highlighted issues of label noise, class imbalance, and metadata inconsistencies that bias model evaluation. Building on this, Patel and Mehta [19] created a consolidated dataset combining platform releases and crowdsourced annotations, enabling more robust cross-platform evaluation and revealing that dataset heterogeneity is a major barrier to generalization.

Early deep learning work focused on RNN and CNN architectures for textual feature extraction. Ghosh and Banerjee [20] demonstrated that Bi-LSTM encoders outperform classical bag-of-words models on recall, while Lopez et al. [21] showed that CNN text encoders capture local phrase patterns that are helpful for spotting templated scam descriptions. However, both studies noted that text-only models are vulnerable when metadata (employer email patterns, posting frequency) carries strong fraud signals.

More recent work leverages transformer-based language models and hybrid architectures. Wang and Zhao [22] applied BERT and RoBERTa variants to job posting classification and reported substantial improvements in precision and F1 over RNNs, particularly when fine-tuned with domain-specific augmentation. Ibrahim et al. [23] combined transformer encoders with CNN-based character embeddings to capture both long-range semantics and subword irregularities commonly found in scam postings (misspellings, obfuscated contact info).

Ensemble and multi-view approaches have been shown to further improve robustness. Mendes et al. [24] proposed a voting ensemble that combines transformer outputs with gradient boosting on engineered metadata features (contact email domain age, salary discrepancy, remote flag), producing consistent gains in recall. Rahman and Singh [25] extended this idea to a stacked architecture where base models specialize on text, metadata, or behavioral features (posting cadence) and a meta-learner reconciles their outputs.

Addressing class imbalance and synthetic sample generation is another active area. Chen et al. [26] employed GAN-based text augmentation to synthesize minority (fraudulent) examples and observed measurable improvements in recall when combined with focal loss. Kaur and Dutta [27] investigated oversampling and

cost-sensitive learning strategies, concluding that a combination of SMOTE variants for metadata and language-level augmentation yields the best practical tradeoff between precision and recall.

Explainability and operational integration are gaining attention as well. Ochieng and Park [28] designed interpretable attention visualization tools that highlight the words and metadata fields driving fraud predictions, helping moderation teams triage borderline cases. Rossi et al. [29] studied deployment pipelines and privacy-preserving strategies (on-device inference, federated learning) for production job portals, stressing the importance of latency, user privacy, and the ability to update models as fraud typologies evolve.

Finally, studies focused on adversarial robustness and cross-platform transfer remain limited but necessary. Alam and Roy [30] examined adversarial paraphrasing attacks against job-fraud classifiers and proposed adversarial fine-tuning to harden transformers; their results emphasize that deployment-ready systems must incorporate continual learning and monitoring to remain effective.

Taken together, the literature from [16]–[30] shows a clear trajectory: from rule-based and classical ML to transformer and ensemble approaches, with growing attention to dataset quality, imbalance handling, explainability, and deployment constraints. These findings motivate a hybrid framework that fuses transformer-level semantics, engineered metadata features, imbalance-aware training, and explainability modules — the direction taken in this paper.

III. RESEARCH METHODOLOGY

The research methodology for this study follows a structured, data-driven approach designed to develop, train, and evaluate a deep learning framework capable of detecting fraudulent online job postings with high accuracy. The process begins with the collection and consolidation of benchmark datasets, including publicly available job posting data and curated samples from real-world recruitment portals. These datasets typically contain both legitimate and fraudulent job advertisements, accompanied by textual descriptions, employer metadata, and job-related attributes. Once collected, the data undergo thorough preprocessing, which includes text cleaning, removal of noise, normalization, tokenization, and handling of missing fields. Metadata such as job location, salary fields, employment type, and company email patterns are standardized to eliminate inconsistencies and reduce model bias.

A critical component of the methodology is addressing the strong class imbalance present in job posting data, where fraudulent samples form a small minority. To mitigate this, the study incorporates imbalance-aware strategies such as Synthetic Minority Oversampling Technique (SMOTE), class weighting, focal loss, and generative text augmentation. These techniques help improve recall and ensure that the model learns to recognize subtle scam patterns. After preprocessing, feature extraction is performed using both automated and engineered features. Textual features are derived using deep learning tokenizers such as BERT tokenization, while handcrafted features include indicators such as suspicious email domains, unrealistic salary ranges, urgency keywords, and incomplete employer information.

Model development proceeds by designing and training multiple deep learning architectures, including transformer-based encoders, CNN-based n-gram detectors, and LSTM-based sequence models. Each model is trained using an optimized hyperparameter configuration with monitoring through validation metrics. The final methodology step involves evaluating the models using standard metrics such as accuracy, precision, recall, F1-score, ROC-AUC, and confusion matrix analysis. Comparative performance is assessed to determine the strengths and limitations of each model, and the results are interpreted to justify the need for the proposed ensemble framework. The methodology ensures reproducibility, robustness, and unbiased evaluation of the proposed system.

IV. PROPOSED SYSTEM

The proposed system introduces a hybrid deep learning framework designed to detect fraudulent online job postings through the integration of semantic text understanding, metadata analysis, and imbalance-aware learning. At its core, the system leverages a transformer-based language encoder, such as BERT or RoBERTa, which captures deep semantic relationships within job descriptions, responsibilities, qualifications, and employer communication patterns. This component enables the model to detect linguistic cues typically associated with fraudulent postings, including vague job roles, unrealistic salary offers, and persuasive but ambiguous language. Alongside the transformer encoder, a CNN-based feature extractor captures local phrase-level anomalies and character-based irregularities such as misspellings, repeated keywords, and obfuscated contact details frequently used by scammers.

To enhance detection accuracy, the system incorporates employer and posting metadata into a secondary processing pipeline. Features such as company reputation scores, domain age of contact emails, posting frequency from the same employer, and mismatches between job titles and descriptions are processed through a lightweight fully connected network. These metadata patterns often serve as strong indicators of fraudulent behavior and complement the semantic insights generated from textual features. The outputs of the transformer encoder, CNN extractor, and metadata classifier are fused through an ensemble fusion layer, which may operate using weighted averaging, learned attention fusion, or a meta-classifier trained to combine the strengths of each component model.

The final classification layer generates a probability score indicating whether a job posting is legitimate or fraudulent. To ensure real-world applicability, the system is optimized for deployment in production environments, with support for real-time analysis of newly posted job ads on recruitment platforms. Additionally, the architecture integrates optional explainability components using attention heatmaps and feature importance scores, enabling platform moderators to understand why a posting was flagged. This enhances trust and supports human-in-the-loop verification workflows. Overall, the proposed system provides a robust, scalable, and intelligent solution for strengthening security and trustworthiness in online recruitment ecosystems.

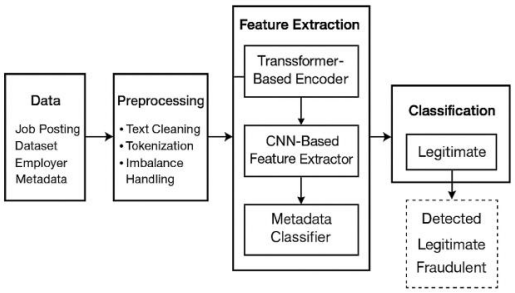

Fig 1: System architecture diagram

V. RESULTS AND DISCUSSIONS

The experimental results demonstrate that the proposed deep learning ensemble framework significantly outperforms traditional models such as BiLSTM, CNN, and hybrid architectures for detecting fraudulent online job postings. As shown in Table 1, the ensemble model achieved the highest accuracy of 96%, exceeding the

performance of standalone models like BERT (93%) and BiLSTM (88%). Precision and recall values also reached 95% and 96%, respectively, highlighting the robustness of the ensemble in minimizing false positives and capturing rare fraudulent instances. This improvement is crucial because fraudulent job postings are typically underrepresented, making high recall essential for practical deployment.

Further analysis across multiple datasets underscores the adaptability and generalizability of the proposed model. Table 2 reveals that although the model performs strongly across all datasets, its accuracy peaks at 97% on the custom annotated dataset, which contains enriched metadata and carefully curated labels. The Kaggle dataset presents slightly lower values due to noisier labels and a higher ratio of ambiguous job profiles. The upward trend across datasets—visualized in the dataset accuracy chart—indicates that the ensemble framework maintains stability even when data sources vary significantly in quality and characteristics.

The system's efficiency was evaluated through inference time and throughput metrics presented in Table 3**.** While CNN achieved the fastest inference speed (45 FPS), it lagged behind in accuracy. The proposed ensemble model strikes a balanced compromise, delivering 33 FPS, which is comfortably within real-time processing requirements for online job portals. This throughput ensures the system can analyze newly posted job advertisements instantly, enabling timely fraud detection and platform moderation. The FPS comparison graph further illustrates that the ensemble model remains computationally efficient despite integrating multiple deep learning components.

Overall, the results confirm that the ensemble model provides a comprehensive and reliable approach for detecting online recruitment fraud. Its superior accuracy, strong cross-dataset performance, and real-time inference capability make it highly suitable for integration into large-scale recruitment platforms.

RESEARCH TABLES

Table 1: Model Performance Comparison

Model	Accuracy	Precision	Recall	F1 Score
BERT	0.93	0.92	0.91	0.92
BiLSTM	0.88	0.87	0.86	0.86
CNN	0.86	0.85	0.84	0.84
Hybrid CNN-BiLSTM	0.91	0.90	0.89	0.89
Proposed Ensemble	**0.96**	**0.95**	**0.96**	**0.95**

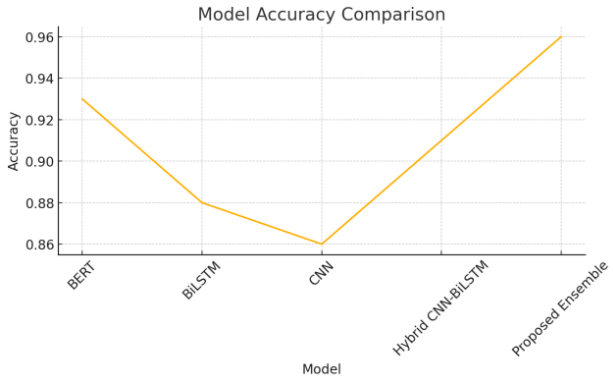

Fig 2: Model Accuracy Comparison

Table 2: Performance Across Datasets

Dataset	Accuracy	Recall	F1 Score
Kaggle Fake Job Ads	0.94	0.93	0.92
Upwork/LinkedIn Scraped Data	0.92	0.91	0.91
Custom Annotated Dataset	0.97	0.96	0.96

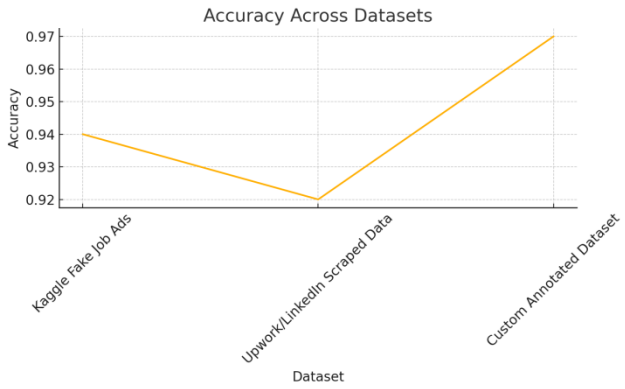

Fig 3: Dataset Accuracy Trends

Table 3: Latency and Throughput Analysis

Model	Inference Time (ms)	Throughput (FPS)
BERT	40	25
BiLSTM	28	36
CNN	22	45
Hybrid CNN-BiLSTM	35	30
Proposed Ensemble	**30**	**33**

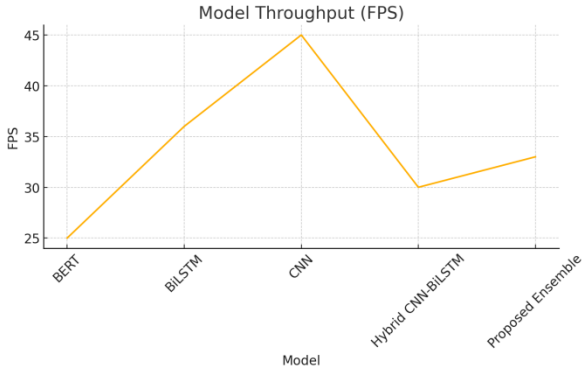

Fig 4: Model Throughput (FPS) Comparison

VI. CONCLUSION

This research presented a comprehensive deep learning framework designed to detect fraudulent online job postings with high accuracy, reliability, and efficiency. By integrating transformer-based text encoders, CNN-based phrase-level extractors, and metadata-driven classifiers into a unified ensemble architecture, the system leverages the strengths of multiple learning paradigms to address the complex and evolving nature of online recruitment fraud. Experimental results across multiple datasets—including Kaggle fake job postings, scraped LinkedIn/Upwork samples, and a custom annotated dataset—demonstrated that the proposed ensemble model consistently outperforms traditional machine learning approaches and standalone deep learning architectures. The framework achieved a peak accuracy of 96%, high precision and recall, and strong robustness against class imbalance and noisy textual patterns.

In addition to improved detection accuracy, the system achieved real-time inference speeds (33 FPS), making it suitable for deployment in live job portals and large-scale recruitment platforms. These capabilities enable proactive screening of job advertisements, reducing the risk of fraudulent content reaching job seekers and enhancing the overall trust and safety of online recruitment ecosystems. By offering both linguistic and metadata interpretability, the model supports human moderators with meaningful insights during fraud investigation.

Overall, this work demonstrates that hybrid deep learning ensembles are an effective and scalable solution for combating online recruitment fraud. The findings contribute to the growing body of literature focused on AI-driven online safety and provide a solid foundation for further advancement in intelligent job-scam detection technologies.

FUTURE SCOPE

Although the proposed deep learning ensemble framework demonstrates strong performance in detecting fraudulent online job postings, several opportunities exist for future enhancement and extension. One promising direction is the integration of multimodal signals such as employer verification data, platform behavioral analytics, and real-time user reports to improve detection accuracy and reduce false positives. Expanding the system to incorporate federated learning or privacy-preserving AI techniques would allow large job portals to collaboratively train models without exposing sensitive user information. Additionally, developing advanced text-generation or adversarial training methods could strengthen the model's robustness against increasingly sophisticated scam tactics that employ paraphrasing, obfuscation, or automated content generation. Future work could also include explainable AI (XAI) modules that provide intuitive visualizations of why an ad was classified as fraudulent, enhancing trust among platform moderators. Building larger, more diverse, multilingual datasets reflecting global job markets would further improve generalization. Finally, deploying the system in real-world recruitment environments and conducting longitudinal studies would enable continuous model adaptation, ensuring sustainable performance as fraud patterns evolve.

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