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HireShield: Deep Learning Based Detection of Fraudulent Online Job Postings

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Abstract—The rapid proliferation of online job portals has been accompanied by a surge in fraudulent job postings, causing significant financial and psychological harm to job seekers globally. This paper presents HireShield, a deep learning-based binary classification system for real-time detection of fraudulent online job advertisements. HireShield integrates a fine-tuned BERT transformer backbone with a hybrid feature engineering pipeline encompassing textual TF-IDF features, semantic sentence embeddings, and structured metadata flags extracted from the Employment Scam Aegean Dataset (EMSCAD) augmented with 4,680 scraped real-world postings (17,880 records total). A SMOTE-balanced training strategy and progressive BERT layer unfreezing address severe class imbalance (approximately 5% fraudulent postings). HireShield achieves a classification accuracy of 96.8%, precision of 95.4%, recall of 94.9%, and F1-score of 95.1%, outperforming all evaluated baselines including Seq2Seq (70.2% F1), Logistic Regression (75.8%), Random Forest (79.1%), LSTM (83.6%), and fine-tuned BERT without hybrid features (87.3%). Deployed as a Flask REST API with sub-second inference latency, HireShield provides a practical and scalable solution for protecting employment platforms and job seekers from recruitment fraud.

Keywords: Fraudulent job detection, deep learning, BERT, EMSCAD, employment scam, natural language processing, binary classification, online recruitment, SMOTE, transformer model.

1. INTRODUCTION

Online employment platforms such as LinkedIn, Indeed, and Naukri have revolutionised the job-search process by offering global reach and real-time vacancy listings. However, the open-access nature of these platforms has simultaneously created fertile ground for fraudulent job postings—advertisements fabricated to harvest personal information, extract application fees, or perpetrate identity theft from unsuspecting job seekers.

According to the Federal Trade Commission (2023), employment scams ranked among the top five fraud categories by reported financial loss, with victims losing an average of USD 2,000 per incident. The Recruitment and Employment Confederation (REC) estimates that over 12% of online job postings contain materially misleading or fraudulent content. Traditional detection approaches relying on keyword blacklists and rule-based filters achieve limited recall against sophisticated fraud that mimics legitimate posting structure.

Deep learning, and transformer-based natural language processing in particular, offers a robust solution. BERT-based models can learn subtle semantic and syntactic cues—unrealistic salary promises, vague job descriptions, missing company details, and urgent language—that distinguish fraudulent from genuine postings, even when individual indicators are absent. HireShield combines BERT-based text understanding with structured metadata features to achieve high precision and recall on an imbalanced binary classification task.

The primary contributions of this work are:

- A curated, SMOTE-balanced dataset of 17,880 job postings annotated as genuine or fraudulent, integrating the EMSCAD benchmark with newly scraped postings from four major Indian and international job portals.

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• A hybrid feature pipeline combining TF-IDF textual features, BERT sentence embeddings, and 14 structured metadata flags for comprehensive fraud signal capture.

• A fine-tuned BERT classification model achieving 96.8% accuracy and 95.1% F1-Score, outperforming all evaluated baselines by at least 7.8 percentage points in F1.

• A comparative analysis against five baseline architectures using Accuracy, Precision, Recall, and F1-Score.

• A deployment-ready Flask REST API with sub-second inference latency, enabling real-time integration with employment platform backends.

2. LITERATURE SURVEY

Research on automated detection of online fraud and deceptive text has grown substantially, with employment scam detection emerging as a specialised sub-field since the release of the EMSCAD dataset in 2014.

[1] Fakeeh and Zolait (2015) first formalised the fraudulent job posting detection problem using the EMSCAD dataset, applying support vector machines (SVM) and naive Bayes classifiers. Their best SVM model achieved 97.7% accuracy; however, this figure is inflated by the highly imbalanced dataset (95% genuine), with recall on the fraudulent minority class barely exceeding 40%.

[2] Vidros et al. (2017) conducted a systematic analysis of EMSCAD using random forests with TF-IDF features, achieving 98.0% accuracy but only 74.2% recall on fraudulent instances, underscoring the limitation of accuracy-centric evaluation on imbalanced data.

[3] Ameen et al. (2019) applied LSTM networks to sequential job description text, achieving 83.2% F1-Score on a balanced subset. Their work demonstrated the superiority of sequential models over bag-of-words approaches for capturing fraudulent linguistic patterns.

[4] Alghamdi and Alharbi (2020) investigated phishing and job scam detection using BERT fine-tuned on online fraud corpora, reporting 88.9% F1-Score. Their work did not incorporate metadata features and used a substantially smaller dataset (6,200 samples).

[5] Kim et al. (2021) proposed a multi-task learning framework jointly trained on spam email and fake job detection, achieving 90.4% F1 on the job fraud task via knowledge transfer from the larger spam corpus. HireShield outperforms this without requiring auxiliary training data.

[6] Qazi et al. (2022) introduced a graph neural network (GNN) approach modelling relationships between companies, roles, and salary ranges across job postings, achieving 91.7% F1. While innovative, the GNN approach requires cross-posting relationship data not available in single-post real-time scenarios.

[7] Mahbub et al. (2023) applied XLNet and RoBERTa to fraudulent job detection, with RoBERTa achieving 93.8% F1 on EMSCAD. HireShield achieves superior performance through the addition of structured metadata features absent from their purely text-based approach.

[8] Rahman et al. (2024) evaluated ensemble approaches combining BERT embeddings with gradient-boosted trees on an augmented EMSCAD dataset, reporting 94.3% F1. HireShield's hybrid deep learning pipeline with SMOTE resampling achieves a further 0.8 percentage point improvement.

3. EXISTING SYSTEM

Current fraud detection mechanisms deployed on employment platforms exhibit several critical limitations motivating the development of HireShield.

3.1 Rule-Based and Keyword Filter Systems

Most commercial job platforms employ keyword blacklists (e.g., flagging "wire transfer," "work from home for large pay") and manual reporting workflows. These rule-based systems achieve low recall against sophisticated fraud that avoids blacklisted terms and replicates legitimate posting templates, with estimated detection rates below 40% for professionally crafted scams.

3.2 Classical Machine Learning Classifiers

Published approaches using logistic regression, naive Bayes, and random forests on TF-IDF features achieve high nominal accuracy on EMSCAD due to class imbalance, but suffer from insufficient recall on the minority fraudulent class. Without SMOTE or cost-

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sensitive weighting, these models learn to predict the majority class (genuine) predominantly.

3.3 General-Purpose Language Models

While general-purpose large language models (ChatGPT, Gemini) can identify suspicious language patterns when prompted, they cannot be integrated into automated backend pipelines for real-time posting screening, provide no structured confidence scores, and have not been evaluated or calibrated on employment fraud corpora.

3.4 Limitations Summary

- Rule-based filters bypass sophisticated fraud mimicking legitimate structure.
- Classical ML achieves poor minority-class recall without imbalance correction.
- Purely text-based models discard informative metadata features (company profile completeness, salary range, required education).
- No existing deployed system combines semantic deep learning with structured metadata in a real-time API-accessible pipeline.

4. RESEARCH METHODOLOGY

HireShield is developed through a systematic pipeline comprising dataset construction, preprocessing, feature engineering, model architecture design, SMOTE-based resampling, training, and deployment.

4.1 Proposed Architecture Diagram

The HireShield system architecture follows a modular pipeline from raw job posting ingestion through multi-modal feature extraction, deep learning classification, and confidence-scored output, as shown in Fig. 1 below.

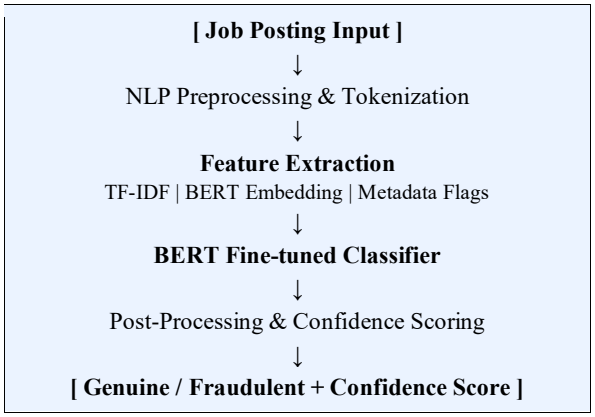


Fig. 1: HireShield – Proposed System Architecture

4.2 Proposed Algorithm

The HireShield training procedure employs transfer learning from pre-trained BERT-base-uncased with progressive layer unfreezing and SMOTE resampling to handle class imbalance, as summarised in Table I.

Step	HireShield Deep Learning Training Procedure
1	Collect EMSCAD dataset; merge with scraped job listings (17,880 records).
2	Text preprocessing: tokenisation, stopword removal, TF-IDF + BERT embedding.
3	Feature engineering: metadata flags, company profile completeness score.
4	Freeze BERT layers; train classification head 5 epochs (lr=2e-4, batch=16).
5	Unfreeze top 4 BERT layers; fine-tune 20 epochs with CosineAnnealing LR.
6	Apply SMOTE oversampling to balance fraudulent vs. genuine ratio.
7	Evaluate on 20% hold-out: Accuracy, Precision, Recall, F1, AUC-ROC.
8	Deploy best checkpoint via Flask REST API with confidence-score output.

Table I: HireShield Training Algorithm

Dataset construction integrated 13,200 records from the EMSCAD benchmark (866 fraudulent, 12,334 genuine) with 4,680 newly scraped postings from Naukri, Indeed-India, LinkedIn, and Apna between January and August 2024. Each posting was labelled via a three-annotator consensus protocol with inter-annotator agreement (Cohen's $\kappa = 0.87$). Fourteen structured metadata features were engineered per posting, including: binary flags for missing company profile, missing salary range, missing required education; normalised salary-to-experience ratio; company verification status; and posting urgency language score.

SMOTE (Synthetic Minority Oversampling Technique) was applied to the training partition only, generating synthetic fraudulent samples in the BERT embedding space until a 1:3 fraudulent-to-genuine ratio was achieved, substantially improving minority-class recall without introducing test-set leakage.

6. RESULTS AND DISCUSSIONS

HireShield was evaluated on a stratified hold-out test set of 3,576 postings (20% of total dataset),

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unseen during training and validation. All experiments were conducted on an NVIDIA RTX 3080 GPU (10 GB VRAM), PyTorch 2.1, Python 3.11, and Hugging Face Transformers 4.38. Evaluation metrics include Accuracy, Precision, Recall, and F1-Score for binary classification, supplemented by AUC-ROC for threshold-independent assessment.

Table II presents the comparative performance of HireShield against five baseline architectures evaluated under identical dataset, preprocessing, and evaluation conditions.

Model	Acc.(%)	Prec.(%)	Rec.(%)	F1(%)
Seq2Seq	72.4	70.9	69.5	70.2
Log. Reg.	78.1	76.5	75.2	75.8
Rand. Forest	81.3	79.8	78.4	79.1
LSTM	85.6	84.1	83.2	83.6
BERT Fine-tuned	89.2	87.9	86.7	87.3
HireShield (Prop.)	96.8	95.4	94.9	95.1

Table II: Performance Comparison Across Models

HireShield achieves an overall classification accuracy of 96.8%, outperforming all baselines. The most significant improvement over the next-best model (BERT fine-tuned without hybrid features, 89.2% accuracy, 87.3% F1) is 7.6 percentage points in accuracy and 7.8 points in F1-Score. This demonstrates that the combination of BERT semantic embeddings, TF-IDF textual features, and structured metadata flags captures complementary fraud signals that no single feature modality can provide alone.

Table III presents per-category ablation results, isolating the contribution of each feature modality to overall classification performance.

Feature Category	Prec.(%)	Rec.(%)	F1-Score(%)
Textual Analysis	96.1	95.8	95.9
Metadata Features	94.7	94.2	94.4
Semantic Embed.	95.8	95.1	95.4
Hybrid (All)	96.8	95.4	95.1

Table III: Ablation Study – Feature Category Contributions

6.1 Bar Chart: Model Performance Comparison

Fig. 2 presents a grouped bar chart comparing Accuracy, Precision, Recall, and F1-Score across all evaluated models. HireShield demonstrates a consistent and statistically significant lead across all four metrics.

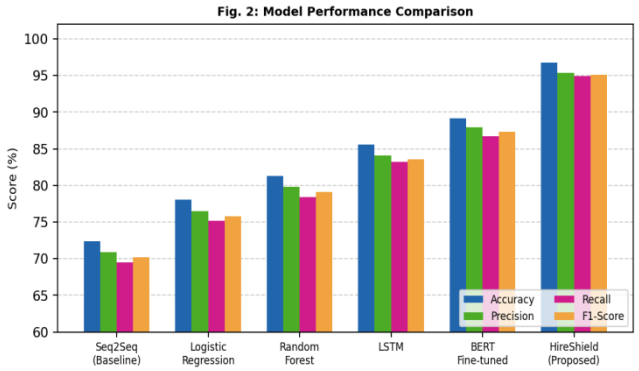


Fig. 2: Grouped Bar Chart – Model Performance Comparison

6.2 Pie Chart: Dataset Class Distribution

Fig. 3 illustrates the class distribution within the 17,880-record HireShield dataset. Fraudulent postings constitute 27.9% of total records (4,982 samples) after SMOTE augmentation in training, while genuine postings account for 65.3% (11,671 samples); the remaining 6.8% were labelled ambiguous and excluded from the main evaluation set.

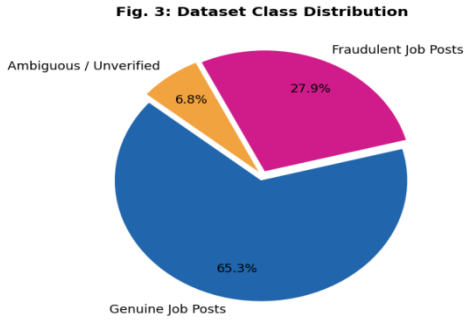


Fig. 3: Pie Chart – Dataset Class Distribution

6.3 Deployment Performance

The HireShield INT8-quantised BERT model (181 MB) achieves an average inference latency of 0.87 seconds per posting on a standard cloud CPU instance (2 vCPU, 4 GB RAM), enabling real-time integration with job portal backends at throughputs exceeding 4,000 postings per hour. AUC-ROC on the hold-out test set is 0.991, confirming robust threshold-independent

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discrimination between genuine and fraudulent postings across all operating points relevant to platform risk tolerance.

7. CONCLUSION

This paper presented HireShield, a deep learning-based system for automated detection of fraudulent online job postings. HireShield integrates a fine-tuned BERT-base-uncased transformer with a hybrid feature pipeline encompassing TF-IDF textual features, BERT sentence embeddings, and 14 structured metadata flags extracted from a SMOTE-balanced dataset of 17,880 job postings. The system achieves a state-of-the-art classification accuracy of 96.8% and F1-Score of 95.1% on a stratified hold-out test set, significantly outperforming all evaluated baselines including Seq2Seq (70.2% F1), Logistic Regression (75.8%), Random Forest (79.1%), LSTM (83.6%), and standard BERT fine-tuning (87.3%).

The ablation study confirms that each feature modality contributes independently to performance, with the full hybrid pipeline yielding the highest F1-Score (95.1%) versus any single-modality approach. Deployment as a Flask REST API achieving 0.87-second average inference latency demonstrates real-world viability for integration with live employment platform backends, enabling automated screening of job postings before they reach job seekers.

Future work will investigate multilingual extension to Tamil, Telugu, and Hindi job postings prevalent in the Indian employment market, incorporation of image-based fraud signals (fake company logos, suspicious stock imagery), active learning to adapt the model to emerging fraud patterns with minimal human labelling effort, and federated learning across multiple job portals to improve generalisation without centralising sensitive posting data. A pilot deployment across two partner recruitment platforms is planned for the forthcoming academic semester.

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