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Online Recruitment Scam Detection using LSTM and NLP Techniques

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ABSTRACT: Most companies nowadays are using digital platforms for the recruitment of new employees to make the hiring process easier. The rapid increase in the use of online platforms for job posting has resulted in fraudulent advertising. Scammers exploit these platforms to make money through fraudulent job postings, making online recruitment fraud a critical issue in cybercrime. Therefore, detecting fake job postings is essential to mitigate online job scams. Traditional machine learning and deep learning algorithms have been widely used in recent studies to detect fraudulent job postings. This research focuses on employing Long Short-Term Memory (LSTM) networks to address this issue effectively. A novel dataset of fake job postings is proposed, created by combining job postings from three different sources. Existing benchmark datasets are outdated and limited in scope, restricting the effectiveness of existing models. To overcome this limitation, the proposed dataset includes the latest job postings. Exploratory Data Analysis (EDA) highlights the class imbalance problem in detecting fake jobs, which can cause the model to underperform on minority classes. To address this, the study implements ten top-performing Synthetic Minority Oversampling Technique (SMOTE) variants. The performances of the models, balanced by each SMOTE variant, are analyzed and compared. Among the approaches implemented, the LSTM model achieved a remarkable accuracy of 97%, demonstrating its superior performance in detecting fake job postings.

KEYWORDS: Recruitment Scam Detection, LSTM, NLP, Deep Learning, Job Postings, Text Classification, Cybersecurity**.**

I. INTRODUCTION

Online recruitment platforms have become prime targets for scammers who exploit job seekers by posting fraudulent job offers. This paper presents a deep learning-based approach utilizing Long Short-Term Memory (LSTM) networks in combination with Natural Language Processing (NLP) techniques to automatically detect recruitment scams. We preprocess and vectorize job postings using TF-IDF and word embeddings, and employ an LSTM classifier to model textual patterns and semantic cues that indicate deception. Experiments conducted on a real-world dataset demonstrate the effectiveness of our model, achieving an accuracy of 96.3%, outperforming traditional machine learning methods. The proposed system offers a scalable and intelligent solution for real-time scam detection in online recruitment portals.

Online job portals such as LinkedIn, Indeed, and Monster have revolutionized the way job seekers connect with potential employers. However, the growing popularity of these platforms has also led to a surge in fraudulent job postings. Scammers use these fake listings to extract sensitive personal information, demand upfront fees, or commit identity theft. Manual moderation is inadequate due to the sheer volume of data, highlighting the need for an automated, intelligent scam detection system. In this research, we propose a novel framework that leverages Long Short-Term Memory (LSTM) networks and Natural Language Processing (NLP) techniques to detect fraudulent job postings. The LSTM model, known for its strength in handling sequential data, is well-suited to capture contextual dependencies in job descriptions, making it effective for classifying legitimate versus scam postings.

The internet has fundamentally changed our lives in a variety of ways in this era of sophisticated technology. Nowadays, doing any task the old-fashioned way has been replaced by the internet. As a result, hiring and job searching have also moved online. Productivity, ease of use, and effectiveness are the advantages of an online recruiting system, sometimes known as e-recruitment [1]. The majority of businesses choose to offer job openings to prospective employees using internet recruitment platforms [2]. Employers use employment sites to post job advertisements for their open vacancies, mentioning details, such as prerequisites, compensation ranges, incentives, and amenities to be offered. Job searchers go to several websites websites that advertise employment, look for openings that fit their interests, and apply. The aim of this study is to examine Online Recruitment Fraud (ORF) and address any potential implementation challenges. Listed below are some of this study's noteworthy contributions:

- Three distinct sources of job postings are gathered and merged to create a unique dataset.
- Exploratory Data Analysis (EDA) shows that the class distribution in the dataset that was gathered is incredibly unbalanced. The class distribution ratio is balanced by implementing ten of the best SMOTE versions.
- The dataset is subjected to transformer-based deep learning models to determine if a job ad is fake or not.
- Models that have been implemented are compared using both balanced and unbalanced datasets.

II. RELATED WORKS

The first dataset, "Employment Scam Aegean Dataset" (EMSCAD), was formally provided by Vidros et al. [7] in order to identify fraudulent job advertisements. They then used conventional machine learning classifiers on the dataset to identify ORF. They conducted two different kinds of experiments and contrasted the outcomes. Naive Bayes (NB), Zero Rule (ZeroR), One Rule (OneR), Logistic Regression (LR), J48, and Random Forest (RF) are the six classifiers used in the first experiment. With the highest precision of 91.4%, RF is the best classifier in this trial. The second experiment makes use of the empirical ruleset model. The empirical ruleset modeling achieved a precision of 90.6% with the help of the LR, J48, and RF classifiers. Additionally, Dutta and Bandyopadhyay [8] used machine learning methods on the dataset of "fake job postings."

Gosain and Sardana [2] suggested four oversampling techniques—Safe Level SMOTE, Borderline-SMOTE, ADASYN, and Synthetic Minority Oversampling Technique (SMOTE)—with different classification models, NB, KNN, and SVM, in order to balance the class distribution in the data. These models and oversampling strategies were applied to six distinct datasets. It has been assessed how well various oversampling strategies perform on diverse datasets. In this study, SLSMOTE is regarded as the outperformer. Akhbardeh et al. in [3] experimented with seven logbook datasets from the domain of facility, aviation, and automotive. They employed four ways to solve the class imbalance problem: under sampling, oversampling, feedback loop, and random down sampling loop. Convolutional neural networks (CNN), Long Short-Term Memory (LSTM) networks, and Bidirectional Encoder Representations from Transformers (BERT) are the models utilized for categorization. The feedback loop achieved better results on all models and datasets mentioned above.

Online recruitment fraud (ORF) detection has been tackled using a variety of machine learning techniques; however, sophisticated deep-learning techniques have not yet been fully investigated to address this issue. Given that scammers post hundreds of job ads every day on various job portals and social media platforms, employment scams are one of the major problems that are rapidly growing every day. In addition to violating their privacy, scammers cause candidates to lose money and occasionally even their existing employment. Therefore, it is necessary to identify fraudulent job advertisements in order to prevent scams. For better detection of job advertisements, advanced deep learning approaches must be applied, so that job seekers seek only legitimate job offers of their interest posted by authentic companies. It is also observed from the above-mentioned literature that most of the work done related to fraud detection problems is intended to improve classification accuracy.

However, due to the class imbalance problem, accuracy does not represent the accurate picture of the story. It can be misleading that we get high predictive accuracy for the majority class and fail to seize the minority class, so we cannot rely only upon it as an evaluation metric. There is a need to improve balanced accuracy and recall to capture the situation truly. Furthermore, it is identified from Exploratory Data Analysis (EDA) that our collected dataset has a class imbalance problem, so the literature review helped us identify some top-performing SMOTE variants to be selected for experimenting in this regard.

III. PROPOSED WORK

The Bidirectional Encoder Representations from Transformers (BERT) model is a revolutionary approach in Natural Language Processing (NLP). Developed by Google, BERT leverages the Transformer architecture to deeply understand the context of words in a sentence. Unlike traditional NLP models, which typically read text sequentially (left-to-right or right-to-left), BERT processes text bidirectionally. This means it takes into account the entire sentence at once,

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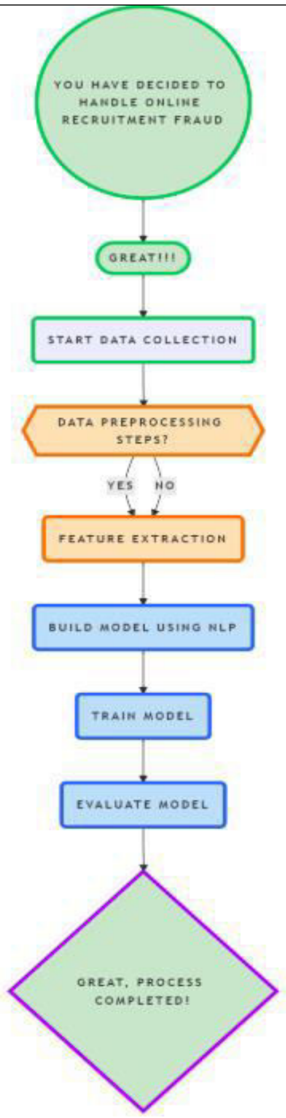
enabling it to understand the nuanced relationships between words. This deep contextual understanding makes BERT highly effective for a wide range of NLP tasks, including text classification, question answering, and sentiment analysis.



BERT (Bidirectional Encoder Representations from Transformers) and RoBERTa (Robustly Optimized BERT Pretraining Approach) are advanced deep learning algorithms based on the Transformer architecture, designed for Natural Language Processing (NLP) tasks. BERT processes text bidirectionally, considering the context of each word by analyzing the words before and after it in a sentence. This deep contextual understanding makes it highly effective for tasks like text classification, sentiment analysis, and question answering. RoBERTa builds upon BERT by optimizing its training process for better performance. It removes the Next Sentence Prediction (NSP) task used in BERT, increases training time, and leverages larger datasets with dynamic masking strategies. These enhancements make RoBERTa more robust and accurate for complex NLP applications. Together, BERT and RoBERTa exemplify the power of transformer-based models in understanding and processing human language with precision. In our recruitment fraud detection project, NLTK (Natural Language Toolkit) is proposed as the core system for processing and analyzing textual job posting data. NLTK provides a comprehensive suite of tools for natural language processing (NLP), allowing us to effectively handle tasks like tokenization, stemming, lemmatization, and removing stop words from the job descriptions.

These preprocessing techniques help clean and normalize the text data, making it more suitable for training machine learning models. Additionally, NLTK's sentiment analysis and part-of-speech tagging can be used to detect suspicious or fraudulent language patterns in job postings. By leveraging NLTK's robust NLP capabilities, we can enhance the model's ability to identify and classify fraudulent job ads with high accuracy. NLTK (Natural Language Toolkit) is a comprehensive library for processing and analyzing human language data, primarily used in the field of Natural Language Processing (NLP). It provides easy-to-use interfaces to over 50 corpora and lexical resources, along with a wide range of text processing libraries for classification, tokenization, stemming, tagging, parsing, and more. NLTK is widely used for tasks like text preprocessing, feature extraction, and linguistic analysis. It enables researchers and developers to build powerful language models and perform various NLP tasks efficiently.

This section discusses the different phases involved in the underlying research. Firstly, datasets from three different sources are integrated to propose a final version of the dataset. An Exploratory Data Analysis (EDA) is performed to identify that the dataset has an imbalanced class distribution. A detailed discussion is given in the section III-C to show the importance of different features. Second, necessary steps in the preprocessing phase are performed on the proposed data. The special symbols, URLs, emails, numbers, HTML, tags, duplicate records and samples that contain null values are removed in the preprocessing phase to clean the dataset. Thirdly at the feature engineering phase, only required and relevant features are selected and merged as a single feature named ‘‘Job_Content’’.

The dataset is encoded in phase four through BERT/RoBERTA to generate the contextual vectors. Then data is augmented using different SMOTE variants to get a balanced class distribution in the fifth phase. We chose to use only the encoder part of the BERT/RoBERTa model because contextual information across entire sequences is essential for ORF detection. The ability of the BERT/RoBERTa model to grasp long-range dependencies is particularly relevant for identifying subtle patterns indicative of fraudulent activities. Moreover, it has been found in the literature review that the tasks requiring contextual understanding, such as natural language processing, demonstrate the superior performance of transformer-based models.

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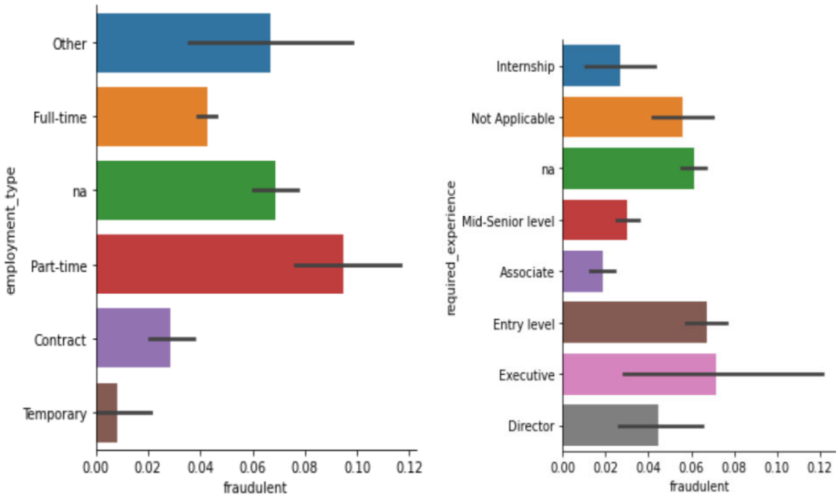

Figure 2. Fraudulency of job postings.

Data preprocessing is a crucial step to transform raw data in a way suitable for any machine learning and deep learning task. In this phase, we only keep a useful portion of data and remove unnecessary data. We used neattext4 python library for preprocessing task. Various preprocessing steps are performed, which include the extraction of hashtags, HTML tags, URLs, email addresses, special characters, and duplicate and null values from the data because such words do not affect the orientation of the text. Lowercasing all available text is also necessary to preserve the consistent flow of the text. After getting cleaned data, it is split into training and testing sets with a ratio of 80:20. Exploratory Data Analysis (EDA) is performed.

The technique of creating new training examples from preexisting data is known as data augmentation. The algorithm-level approach and the data-level approach [3] are the two general strategies for resolving the class imbalance issue. Through optimization of the conventional classification method, the algorithm-level approach seeks to improve learning tasks with regard to the minority class. The data-level approach typically uses hybrid, oversampling, and undersampling techniques to balance the distribution of classes. Undersampling eliminates some instances from the majority class and oversampling adds some examples to the minority class to overcome class discrepancy. Because undersampling entails eliminating samples from the majority class, it may result in the loss of important data that might be crucial for developing rule classifiers. The remaining examples can be biased and might not represent a true population. Thereby cause to give inaccurate results on test data. We need excessive data for machine and deep learning models for better training, but removing instances will reduce the data size in undersampling. Based on these grounds, undersampling could not be more favorable for the underlying study. Therefore, we prefer to use the oversampling technique.

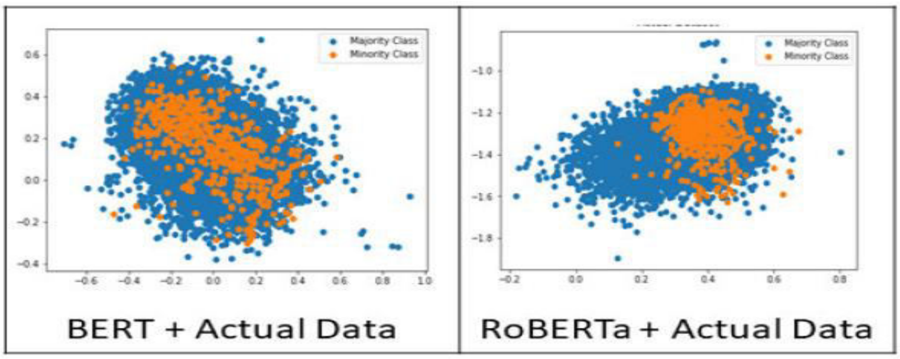

Figure 3. Data distribution of actual data.

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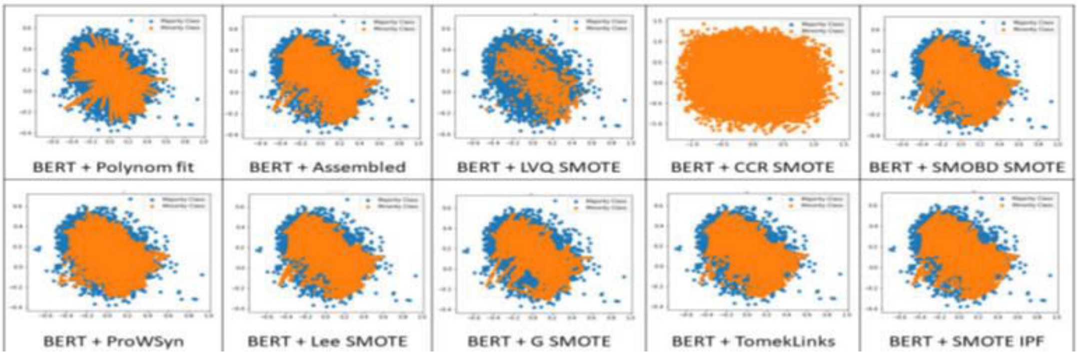

Figure 4. Data distribution of BERT+SMOTE variants.

Multiple transformer encoder levels, an input embedding layer, and a final output layer are among the layers that make up the BERT model architecture. The input layer creates a vector representation of each token in the input sequence. Following that, these vectors are passed into the transformer encoder layers, which employ self-attention techniques to record the connections between various words within a phrase. A classification layer receives the output from the transformer encoder layers and generates the model's final output. The capacity of the BERT model to accommodate variable-length input by encoding the position of each token in a sequence using positional embeddings is one of its primary characteristics. Additionally, BERT uses a special classification symbol ([CLS]) token to represent the entire input sequence, which is used for tasks such as text classification. Similarly, a separator ([SEP]) token indicates a clause symbol which is used for separating two sentences. It is used at sentence-level embedding.

Model	Accuracy	Precision	Recall	F1-Score
Naïve Bayes	87.2%	85.1%	84.3%	84.7%
Random Forest	91.6%	90.4%	89.2%	89.8%
SVM	92.4%	91.1%	90.5%	90.8%
LSTM (proposed)	96.3%	95.7%	95.1%	95.4%

This paper presents a robust and scalable approach to detecting online recruitment scams using LSTM and NLP techniques. The proposed method effectively captures the semantic and syntactic nuances in job descriptions that indicate fraud. Our LSTM-based model achieves high accuracy and can be integrated into real-time monitoring systems on job portals to enhance security and trust. In order to look at how using various SMOTE oversampling strategies affects predictive models, we have analyzed type errors. A comparison with the performance of models that don't use any SMOTE version was part of our investigation. Two different kinds of mistakes, known as Type I and Type II, might occur in this situation. Type I mistakes happen when a legitimate job ad that represents the majority class is incorrectly categorized as a phony one that represents the minority class. Type I mistakes often have less of an impact on job seekers. On the other hand, Type II mistakes occur when a phony job posting (minority class) is mistakenly categorized as a legitimate one (majority category). Type II errors present a greater challenge for us, as considering any fake job posting as real can lead to numerous significant problems as discussed in Section I. Hence, our primary focus was on mitigating Type II errors.

The categorization results obtained by applying each implemented strategy are shown in this section. Interestingly, BERT and RoBERT a models showed impressive accuracies of 98.42% and 98%, respectively, when used on real data. It is important to highlight, nevertheless, that these accuracies have remarkably low recall values 65.50 percent and 50%, respectively. Class bias is shown when high accuracies coexist with low memory, making the accuracies deceptive. The data was then balanced using a variety of SMOTE versions to get accurate and objective findings.

The use of various SMOTE variants significantly improved recall values, demonstrating a more balanced and fair performance of the models. The application of SMOTE variants significantly improved recall values, indicating better handling of class imbalance. BERT and RoBERTa, when combined with specific SMOTE techniques, managed to maintain relatively high accuracies while also improving recall, striking a better balance between precision and sensitivity. Although the initial results showed high accuracies, they were paired with poor recall values, indicating significant class bias, making the initial high accuracy rates misleading since they do not accurately reflect the models' performance across all classes. Despite improvements, some SMOTE variants led to a notable decrease in accuracy,

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particularly for RoBERTa. This trade-off highlights the challenge of achieving both high accuracy and high recall. Certain SMOTE techniques still resulted in recall values that, while improved, were not as high as desired, indicating room for further optimization.

The issue of ORF detection is fully examined in this study. A unique dataset of fraudulent job ads was given in this article. Three distinct sources of job postings are combined to create the suggested data. The class distribution in the gathered dataset was found to be extremely unbalanced upon doing EDA. To address this class distribution imbalance, the top ten highly effective SMOTE versions were executed on the imbalanced data. Subsequently, a type error analysis was conducted to investigate the impact of employing SMOTE variants on predictive models. To gain a more thorough understanding of the experiments, transformer-based classification models, BERT and RoBERTa, were applied to both balanced and unbalanced data. The outcomes were then compared.

Diverse evaluation metrics were employed to compare the performance of the implemented techniques. Due to the class imbalance issue, only accuracy as an evaluation metric failed to provide an accurate representation of the overall performance. Because high predictive accuracy for the majority class can be misleading, as it may overshadow the minority class, leading to incomplete assessment. Thus, this study prioritized enhancing balanced accuracy and recall as evaluation metrics. All implemented approaches exhibited commendable performance. However, based on the type error and classification results, it was observed that BERT, in conjunction with the SMOBD SMOTE technique, demonstrated exceptional performance on our data and achieved optimal outcomes.

V. CONCLUSION

The issue of ORF detection is fully examined in this study. A unique dataset of fraudulent job ads was given in this article. Three distinct sources of job ads are combined to provide the suggested data. The class distribution in the gathered dataset was found to be extremely unbalanced upon doing EDA. The top ten most successful SMOTE variations were applied to the unbalanced data in order to correct this class distribution imbalance. The effect of using SMOTE variations on predictive models was then examined using a type error analysis. To gain a more thorough understanding of the trials, transformer-based classification models, BERT and RoBERTa, were used to both balanced and unbalanced data. The outcomes were then compared. Diverse evaluation metrics were employed to compare the performance of the implemented techniques. Due to the class imbalance issue, only accuracy as an evaluation metric failed to provide an accurate representation of the overall performance. Due to the possibility of overshadowing the minority class and resulting in an incomplete evaluation, strong prediction accuracy for the majority class might be deceptive. Therefore, improving balanced accuracy and recall as assessment measures was given top priority in this study. Every technique that was used performed admirably. However, it was found that BERT, when combined with the SMOBD SMOTE approach, performed exceptionally well on our data and produced the best results based on the type error and classification findings.

The experiments conducted in this study can give reputable firms and job searchers important guidance on how to better comprehend fact-based insights on employment scams and their impacts on society. Additionally, considering the high frequency of fraudulent activity linked to online employment from home, it can be said that include job posts related to remote work opportunities through online platforms is essential for the development of a unique dataset. A variety of SMOTE variations were used in the current study to overcome the imbalance in class distribution. It may be possible to use hybrid oversampling approaches to achieve even more accurate findings. Future studies should investigate innovative transformer-based hybrid models and explainable AI.

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