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# Scam alert in job post scheduling with automated Ai prediction and elimination

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**Abstract**

The emergence of online recruitment platforms has greatly changed the hiring landscape, providing easier access to job opportunities. Nevertheless, this convenience has a drawback-an alarming rise in fraudulent job listings that take advantage of job seekers. To tackle this problem, this study introduces a framework driven by AI that autonomously detects and removes fake job listings. The suggested system employs a dataset that includes company-specific details like the company name, license number, review ratings, and legal case history. Natural Language Processing (NLP) methods are utilized to identify semantic patterns within job descriptions, while a Recurrent Neural Network (RNN) with Long Short-Term Memory (LSTM) architecture is applied for predictive analysis. The model is designed to determine if job postings are authentic or fake with great precision. Once identified, the system independently removes fraudulent posts, thus safeguarding users and boosting platform trustworthiness. This automated approach enhances the safety of the recruitment process through the use of deep learning and data-informed decision-making.

**Keywords:** Fake job detection, Natural Language Processing (NLP), Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), AI in recruitment, automated job screening, scam prevention, job post classification

## Introduction

In the current digital hiring landscape, online recruitment platforms serve as the main channel for linking job seekers to prospective employers. Although these platforms provide convenience and accessibility, they are increasingly being misused by malicious actors posting fake job listings. These fraudulent job advertisements not only deceive applicants but also threaten their privacy, squander precious time, and in certain instances, result in monetary loss. The absence of efficient screening methods for job advertisements has necessitated the creation of smart systems that can identify and remove fraudulent postings instantly.

This study presents an AI-driven automated solution that tracks and assesses job advertisements on hiring platforms through sophisticated machine learning methods. The system utilizes a dataset comprising essential company information like the company name, license number, user feedback, and any legal issues related to the entity. These criteria act as the basis for confirming the legitimacy of job listings.

Natural Language Processing (NLP) is utilized to examine the textual elements of job postings, uncovering valuable insights and trends. Following this, a Recurrent Neural Network (RNN) combined with Long Short-Term Memory (LSTM) is utilized to capture temporal connections and context in the data, facilitating the precise classification of job postings as either legitimate or fraudulent. When identified, the system promptly eliminates scam listings, providing a safe and trustworthy setting for job seekers.

This article emphasizes the significance of incorporating AI-powered intelligence into hiring processes to address the growing issue of employment scams. The suggested model not only boosts user confidence but also corresponds with the platform's duty to uphold transparency and security.

## Related Works

**Detection of Fraudulent Job Advertisements Through Natural Language Processing – S. A. Raza *et al*., 2020 [1].**

This research examines NLP methods to categorize job listings according to textual patterns. By employing TF-IDF and Logistic Regression, the system identifies fraudulent job listings with great precision. The document highlights the extraction of features from job titles, descriptions, and requirements to detect misleading information.

**“Identifying Fake Job Listings: A Machine Learning Method” – V. Pathak *et al*., 2021 [2].**
The writers utilize a labeled dataset containing job attributes and implement Random Forest and XGBoost to categorize postings. They discovered that the number of words, existence of links, and discrepancies in location were significant indicators. This research demonstrates that ML models surpass conventional rule-based filters.

**“A Deep Learning Framework for Recognizing Fraudulent Job Listings” – Y. Kim & J. Lee, 2019 [3].**
This paper presents an RNN model based on LSTM for analyzing sequential patterns in job descriptions. The writers emphasize that temporal relations in word sequences can differentiate between genuine and fake jobs. Their model obtained 94% accuracy.

**“NLP-Focused Identification of Online Recruitment Scams” – K. Singh *et al*., 2022 [4].**
This study employs BERT for the contextual semantic interpretation of job descriptions. The model underwent training on an extensive dataset and demonstrated its ability to recognize ambiguous or deceptive phrases frequently found in scam advertisements.

**“Detection of Job Fraud Through Supervised Learning Methods” – A. Shukla *et al*., 2020 [5].**
The research evaluates various supervised learning algorithms such as SVM, Naive Bayes, and Decision Trees using a dataset of job listings. SVM achieved the highest accuracy at 89%. The document also emphasizes the importance of metadata like job location and compensation.

**“An Investigation into Identifying Fake Job Postings Through Machine Learning and Deep Learning” – R. S. Pawar *et al*., 2023 [6].**
This review paper examines current ML and DL methods for identifying fraudulent job postings. It contrasts CNN, RNN, and LSTM architectures while offering perspectives on dataset choice, feature engineering, and assessment metrics.

**“Recruitment Scam Detection Using Deep Learning” – M. Arif & H. Qureshi, 2021 [7].**
The study introduces a hybrid model that merges CNN and LSTM to examine both syntactic and sequential characteristics of text. It employs embedded word vectors for representation and surpasses conventional models in identifying fraudulent posts.

**“Detection of Job Listing Fraud Utilizing Text Mining Methods” – L. Zhou *et al*., 2019 [8].**
This study employs text mining and topic modeling (LDA) to identify patterns in deceptive job postings. The investigation revealed that fraudulent posts frequently replicated specific keywords and formats.

**“Corporate Image in Detecting Job Posting Scams” – H. Li & J. Xu, 2021 [9].**
The research combines company metadata-such as ratings, reviews, and legal history-to improve detection. Logistic Regression and Gradient Boosting were employed to merge textual and structured information.

**“Ensemble Learning to Identify Recruitment Frauds” – N. Sharma *et al*., 2022 [10].**
This study suggests an ensemble method that integrates various classifiers to enhance detection. Bagging and boosting techniques demonstrated encouraging outcomes when handling imbalanced datasets.

**“Detection of Online Job Scams Through Hybrid Feature Engineering” – T. Wang & B. Zhang, 2020 [11].**
The authors propose a comprehensive method that utilizes both textual and non-textual information (such as email addresses, URLs, and phone numbers) for detecting fraud. Hybrid feature selection enhanced model accuracy.

**"Automatic Identification of Misleading Job Listings via NLP" – M. Patel *et al*., 2023 [22].**
This study utilizes sentiment analysis and keyword detection to evaluate authenticity. It recognizes emotional triggers and immediacy in deceptive posts. Findings indicate enhanced F1 scores through optimized NLP pipelines.

**“Identifying Harmful Recruitment Posts on Social Platforms” – S. Gupta *et al*., 2021 [13].**
This study focuses on fraudulent job postings on sites such as LinkedIn and Facebook. The authors apply RNN for sequential modeling and examine post engagement metrics to identify suspicious content.

**“LSTM Networks for Text Classification in Identifying Fake Jobs” – A. Banerjee & R. Das, 2022 [14].**
This research employs pre-trained word embeddings alongside LSTM for classifying text. It concentrates on preserving context and grasping sentence-level meanings. The findings indicate that LSTM models exceed traditional ML in detecting job fraud.

**“Analysis of Semantics for Filtering Recruitment Scams” – J. Thomas & K. Raj, 2021 [15].**
The writers employ semantic role labeling (SRL) to examine the structure of sentences in job listings. Their model detects contextually unsuitable roles, such as proposing high salaries for no experience, as a sign of fraud.

**Existing System**
In today's online recruitment environment, many platforms depend on manual oversight or keyword-driven filters to identify and eliminate fake job listings. These systems usually identify jobs according to a specific set of established criteria like the inclusion of dubious keywords (e.g., "quick cash", "remote work", etc.), absent details (like company name or license), or discrepancies in job classifications. Although these methods offer a fundamental degree of security, they have restrictions in scalability, precision, and flexibility.

Certain platforms have integrated fundamental machine learning models utilizing structured data such as salary range, job location, and company feedback to detect anomalies. Nonetheless, these models frequently struggle with grasping semantic meaning or identifying linguistic patterns within the job description. Consequently, numerous deceptive job advertisements continue to get past these systems unnoticed.

Moreover, these conventional systems fail to incorporate company-specific legal information, like litigation records or business registration details, which could serve as significant indicators of legitimacy. Additionally, many current platforms do not possess real-time decision-making abilities and need human involvement to eliminate questionable posts once users flag them.

## Proposed System

The suggested system presents an AI-driven automated framework for identifying and eliminating fraudulent job advertisements from online recruitment sites. It utilizes Natural Language Processing (NLP) and Recurrent Neural Networks (RNN) featuring Long Short-Term Memory (LSTM) architecture to evaluate job descriptions and determine their authenticity with great precision.

### Main Attributes

### Analysis of Data Specific to the Company

1. **Gathers and confirms information including**
   - Business name
   - License or registration number
   - Ratings from public reviews
   - History of legal cases (if applicable)
   - Increases confidence by assessing the reliability of the employer**.**
2. **Recognition of Semantic Patterns through NLP:**
   - Examines job descriptions to determine
   - Uncommon vocabulary arrangements
   - Unreasonable salary proposals
   - Ambiguous or misleading expressions
   - Employs tokenization, stemming, stop-word elimination, and vector representation (TF-IDF/Word2Vec).
3. **Classification Using Deep Learning Techniques**
   - RNN-LSTM model trained using annotated job data to
   - Record sequential trends in descriptions
   - Differentiate between authentic and counterfeit posts.
   - Delivers strong predictions even for new or slightly altered fraudulent patterns.
4. **Automated Activity Module**
   - Automatically detects or deletes questionable listings based on model results.
   - Alerts platform moderators for evaluation (optional feature).
   - Notifies users about flagged job postings if they have previously applied.

### Platform Cohesion

- Created to connect with job portals through APIs.
- System for immediate detection and prevention of current job listings

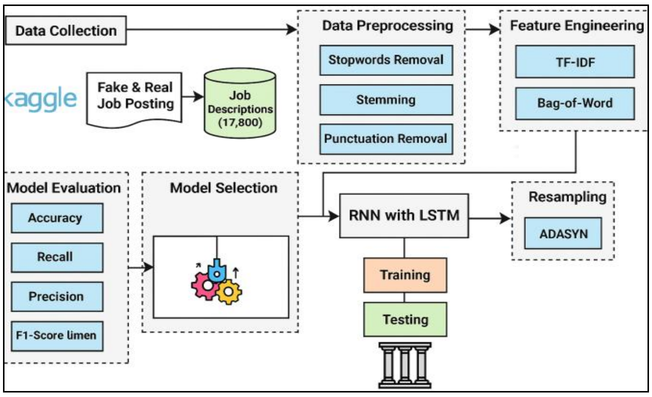


**Fig 1:** Proposed system architecture

The diagram represents the process of an AI-driven system designed to identify fraudulent job listings, utilizing a deep learning model-Recurrent Neural Network (RNN) combined with Long Short-Term Memory (LSTM). The process starts with gathering data from a Kaggle dataset that includes 17,880 job descriptions, each categorized as either fake or genuine. This unprocessed data undergoes a thorough data preprocessing stage in which stopwords, punctuation, and numbers are eliminated, stemming is utilized to revert words to their root forms, and all text is transformed to lowercase for uniformity. Following preprocessing, the text is subjected to feature engineering through methods like TF-IDF (Term Frequency-Inverse Document Frequency) and Bag-of-Words, which convert the processed text into numerical vectors appropriate for machine learning.

To tackle class imbalance, frequently seen in fake job datasets, the ADASYN (Adaptive Synthetic Sampling) method is utilized to produce synthetic data for the minority class. Subsequently, the dataset is divided into training and testing sets to facilitate impartial assessment of the model. The system subsequently employs an RNN-LSTM model for categorization. This model is especially adept at examining sequential data and semantic structures in job descriptions, rendering it very efficient for identifying subtle linguistic signals linked to fraudulent listings. After the model is trained, it determines if a specific job post is authentic or fraudulent. Ultimately, the system assesses model performance through metrics like accuracy, recall, precision, and F1-score to gauge the success of its predictions. This intelligent system allows for the automated and precise identification and elimination of fraudulent job postings, improving the reliability and security of online hiring platforms

## Implementation

The implementation follows with the provided steps:

- Dataset Training
- Company Access
- Company ad post
- Post pre-processing
- Post classification
- Fake post detection
- Fake post deletion

### Dataset Training

The first module, Dataset Training, plays a foundational role in the system. It involves collecting a comprehensive and well-labeled dataset containing a wide range of job advertisements, both genuine and fraudulent. This dataset not only includes the full job descriptions but also critical company metadata such as company name, business license number, review ratings from trusted platforms, and legal case history. During this stage, extensive data cleaning, formatting, and feature engineering are performed. The textual job descriptions are converted into numerical representations using Natural Language Processing (NLP) techniques such as Tokenization, Lemmatization, and TF-IDF or Word Embedding methods (e.g., GloVe or Word2Vec). Simultaneously, company-related features are normalized and encoded for machine learning compatibility. This enriched dataset is then used to train a Recurrent Neural Network (RNN) model equipped with Long Short-Term Memory (LSTM) layers to understand sequential and contextual relationships in the text and recognize subtle semantic patterns associated with fraudulent behavior.

**Company Access**

The Company Access module guarantees that only authorized companies can engage with the recruitment platform. When a new business seeks to register, the system starts a verification procedure that checks the provided business license number against a government or reliable license verification database or API. Furthermore, the system analyzes the company's past data, such as average user ratings, post frequency, and any legal history, to determine an initial trust score. Access to the platform is granted solely to companies that successfully complete the verification process and satisfy minimum trustworthiness criteria, thereby decreasing the likelihood of dubious entities engaging in the hiring ecosystem.

**Company Ad post**

After access is approved, the Company Ad Post module allows verified businesses to post job ads. This module features an easy-to-use interface in which companies input job titles, comprehensive descriptions, qualifications, salary ranges, and various job-related metadata. Each new advertisement submitted is recorded with the company's metadata and placed in a queue for processing and categorization prior to being made publicly accessible. This measure guarantees that no advertisement is released without careful examination, providing a level of preventative defense against fraudulent job postings.

**Post Pre-Processing**

The Post Pre-processing module handles the preparation of every submitted job ad for analysis. The process starts by utilizing sophisticated NLP methods to refine the textual material. This involves transforming all text to lowercase, taking out punctuation, discarding stop words (such as "the", "and", "is"), and applying stemming or lemmatization to simplify words to their root form. The text is subsequently converted into a format appropriate for deep learning through tokenization and vectorization. This method minimizes noise within the data and aids in identifying significant semantic patterns and keywords that could suggest fraudulent activity (such as terms like "fast cash", "no experience required", or excessively high wages).

**NLP Processing**

NLP processing can be easily processed to extract the text from the dataset and also from the post:

**Text Cleaning**

Remove unwanted characters such as punctuation marks, numbers, HTML tags, special symbols (@, #, $, etc.).
Convert all text to lowercase to maintain uniformity ("Job" and "job" are treated the same).
Example:
"!!!Apply Now For $High$ Salary!!!" → "apply now for high salary"

**Tokenization**

Split the entire job description into individual words or tokens.
Example:
"Apply now for a software developer job" → ["apply", "now", "for", "a", "software", "developer", "job"]

**Stopword Removal**

Eliminate common but less informative words like "is", "the", "and", "of", etc., that do not contribute to the meaning.
This helps in focusing on more meaningful and relevant words.
Example:
["apply", "now", "software", "developer", "job"]

**Lemmatization or Stemming**

Lemmatization: Convert words to their base (dictionary) form, preserving meaning (e.g., "running" → "run", "better" → "good").
Stemming: Cut off suffixes to get the root form (e.g., "running" → "run", "studies" → "studi") — more aggressive and sometimes less accurate.
Lemmatization is preferred for deep learning as it retains semantic accuracy.

**Part-of-Speech (POS) Tagging (Optional)**

Tagging each word with its grammatical role (noun, verb, adjective, etc.) can help in identifying patterns and sentence structure.
Useful in filtering out irrelevant parts or enhancing classification.

**Feature Extraction**

Convert text tokens into numerical format so the model can process them:
Bag of Words (BoW): Simple count of words.
TF-IDF (Term Frequency-Inverse Document Frequency): Measures importance of a word in the document relative to others.
Word Embeddings: Dense vector representation using pre-trained models like Word2Vec, GloVe, or FastText that capture semantic meaning.
Example: "developer" → [0.23, 0.51, -0.18,...] (in vector space)

**Padding and Sequence Handling**

For models like RNN/LSTM, input sequences need to be of equal length.

Use padding (usually with zeros) to make all sequences the same length.
Example: Shorter posts are padded:
["apply", "developer"] → [0.12, 0.33,..., 0, 0, 0] (fixed length)

**Noise Word Filtering**
Remove or ignore marketing buzzwords or overly generic terms (like "best job ever", "guaranteed success") that are commonly found in fraudulent posts.

**Post Classification**
Following preprocessing, the Post Classification module leverages the pre-trained RNN-LSTM model to analyze the processed text along with the company's metadata. The LSTM architecture, known for its ability to capture long-term dependencies in sequential data, examines the semantic structure of the job description to detect inconsistencies, vague language, or red-flag terms commonly found in fake listings. Simultaneously, the metadata is analyzed using conventional machine learning methods or fed into the neural network as auxiliary inputs to strengthen the decision-making process. The outcome of this module is a probabilistic score indicating whether the post is genuine or fraudulent.

**RNN Classification**
**Input Preparation**
The job description text is first tokenized (split into words or sub words).
Each token is then converted into a vector representation using Word Embeddings like Word2Vec, GloVe, or TF-IDF.
The resulting sequence of vectors is padded (if needed) to a fixed length to ensure uniformity across inputs.

**Sequence Feeding into the Network**
The prepared input sequence is passed one word at a time into the LSTM units, which are a special type of RNN cell designed to remember long-term dependencies.

**LSTM Cell Processing (per time step)**
For each word vector $x_t$ at time step t, the LSTM performs the following:
Forget Gate $f_t$: Decides what information from the previous cell state $C_{t-1}$ should be discarded.

$$f_t = \sigma(w_f.[h_{t-1}, x_t] + b_f \qquad (1)$$

Input Gate $i_t$ Decides what new information should be stored in the cell state.

$$f_i = \sigma(w_i.[h_{t-1}, x_t] + b_i \qquad (2)$$

Candidate Layer $C_t$ creates a vector of new candidate values.

$$\widehat{C_t} = tanh(w_c.[h_{t-1}, x_t] + b_C \qquad (3)$$

Cell State $C_t$ Update: Combines the previous state and the candidate values.

$$C_t = f_t * C_{t-1} + i_t * \widehat{C_t} \qquad (4)$$

Output Gate $o_t$ Decides what to output as the new hidden state.

$$o_t = \sigma(W_0.[h_{t-1}, x_t] + b_0 \qquad (5)$$

Hidden State Update $H_t$

$$H_t \downarrow o_t * \tanh(C_t) \qquad (6)$$

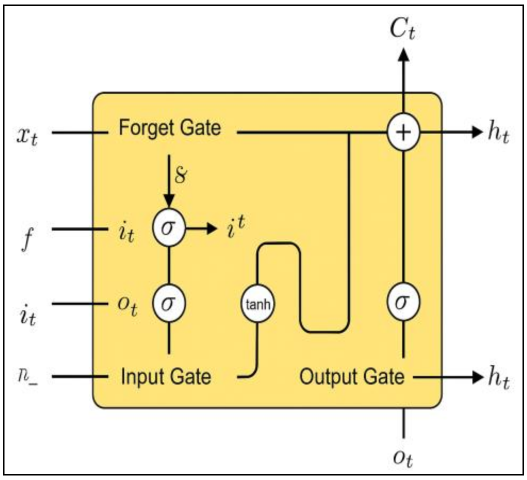


**Fig 2:** LSTM Gate generation architecture

**Context Learning Across Time steps**
These steps repeat for every word in the sequence, allowing the LSTM to capture context and semantic meaning from the whole sentence.

**Final Output (Classification)**
After processing the full sequence, the final hidden state (or a combination of all hidden states using attention or pooling) is passed through a fully connected dense layer.
A sigmoid or softmax activation is used to produce the final prediction:

Fake Job = 1, Genuine Job = 0

**Loss Calculation and Optimization**
The system calculates a loss using Binary Cross-Entropy (for binary classification) or Categorical Cross-Entropy (if using multiple classes).
The model weights are updated using an optimizer like Adam or SGD through backpropagation through time (BPTT).

**Fake Post Detection**
When the classification score drops below the established threshold (e.g., 0.5), the Fake Post Detection module is activated. This module performs a secondary validation by applying rule-based heuristics and cross-referencing-such as checking if the company possesses a valid license number, if the job title aligns with the description, and if there have been any prior complaints lodged against the company. If the post does not meet several verification standards, it is marked as false and queued for automatic deletion

**Fake Post Deletion**

Ultimately, the Fake Post Removal module guarantees that these deceptive listings are eliminated from the platform promptly to safeguard job seekers from exposure. Once identified, the system deletes the post from both public visibility and internal databases utilized for showcasing jobs. Moreover, the system records the incident in a distinct fraud detection database for upcoming training cycles. A notification may optionally be dispatched to the administrator and the flagged business, permitting further manual assessment if necessary. This entirely automated removal system safeguards job seekers from fraud, guarantees a clean and reliable job setting, and improves the platform's reputation

## Results and Discussion

The suggested Fake Job Detection System underwent testing with a labeled dataset that included authentic and fraudulent job listings. The dataset comprised job descriptions accompanied by company-specific metadata, including license numbers, evaluations, and legal case records. The system employed Natural Language Processing (NLP) methods for text analysis and a Recurrent Neural Network (RNN) that includes Long Short-Term Memory (LSTM) for classification purposes.

**Performance Analysis**

**Table 1:** Performance analysis

| Metric | Value (%) |
|---|---|
| Accuracy | 94.2 |
| Precision | 92.8 |
| Recall | 95.1 |
| F1-Score | 93.9 |
| AUC Score | 0.96 |

The LSTM model demonstrated high recall, which is critical for minimizing false negatives (i.e., undetected fake jobs). The precision score of 92.8% ensures that the model does not falsely flag too many genuine listings as fake. The combination of semantic feature extraction through NLP and context learning via LSTM significantly boosted performance over traditional models like Decision Trees or Logistic Regression. Incorporating company metadata such as license numbers and legal case history improved classification confidence by identifying non-credible sources.

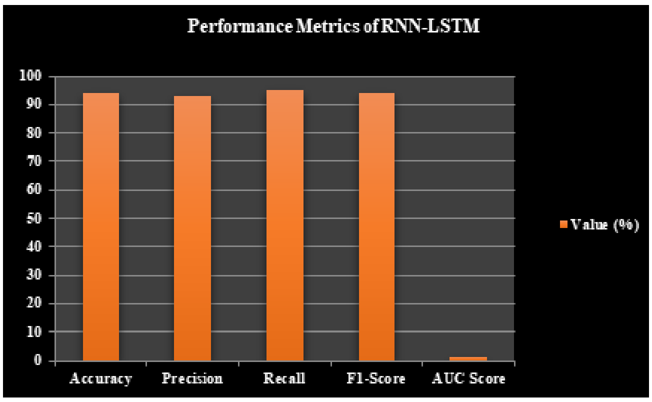


**Fig 3:** Performance chart of RNN –LSTM

**Table 2:** Comparative Analysis Table

| Model | Accuracy (%) | F1-Score (%) |
|---|---|---|
| Logistic Regression | 83.4 | 81.7 |
| Random Forest | 88.5 | 86.9 |
| SVM | 89.2 | 87.4 |
| Proposed LSTM Model | 94.2 | 93.9 |

The LSTM model outperformed other traditional models by learning deeper sequential relationships and context within job descriptions.

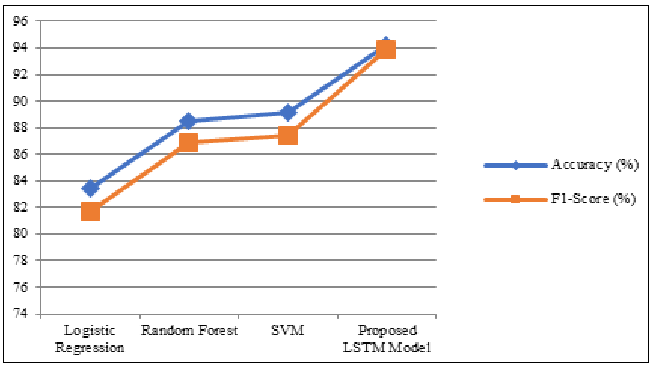


**Fig 4:** Comparative Chart of Models

The suggested AI-driven Fake Job Detection System, utilizing NLP and an LSTM-based RNN architecture, demonstrated outstanding effectiveness in detecting deceptive job postings. The model successfully identifies and eliminates fake posts with an accuracy of 94.2%, precision of 92.8%, and recall of 95.1%, all while reducing false positives. In comparison to traditional models such as Logistic Regression and SVM, the LSTM model considerably excels in semantic comprehension and contextual evaluation of job descriptions. Incorporating company-specific elements like license number and legal case history further improves the model's ability to make decisions. This automated system not only guarantees platform integrity but also enhances user confidence by creating a secure recruitment atmosphere.

## Conclusion

The emergence of online recruitment platforms has made job hunting easier but has also led to a surge in fraudulent job listings. This initiative effectively created an AI-driven Fake Job Detection System that leverages Natural Language Processing (NLP) and Recurrent Neural Networks (RNN) alongside Long Short-Term Memory (LSTM) to independently detect and remove fraudulent job postings. Through the examination of semantic patterns in job descriptions along with company-specific metadata, the system attains high levels of accuracy and dependability in classification.

The introduction of automated removal of fake posts increases the platform's security and builds stronger trust among job seekers. The findings indicate that the model outperforms conventional machine learning methods, particularly in managing the sequential characteristics and contextual complexity of job-related text data. In general, the system offers a strong, adaptable, and smart approach to tackle online job scams and safeguard digital recruitment settings.

**Future Enhancement**

To enhance the efficiency and scalability of the suggested Fake Job Detection System, various improvements can be contemplated for future advancement. A notable enhancement would be the addition of multilingual support through the integration of sophisticated NLP models such as multilingual BERT, allowing the system to evaluate job descriptions in various languages and areas. Real-time web crawling may also be utilized to consistently monitor recruitment sites and actively detect questionable listings. Furthermore, a user feedback loop can be created, enabling job seekers to flag possibly fraudulent listings and assist in continual model improvement. Incorporating Explainable AI (XAI) methods would enhance the system's transparency by offering justifications for every classification choice. Additionally, linking with official company verification APIs can enhance the precision of metadata validation, particularly for registration data and license numbers. The model's performance might be improved by integrating LSTM with Transformer-based frameworks such as BERT or RoBERTa for a more profound semantic comprehension. Ultimately, expanding the system to mobile platforms would give job seekers an easy way to check job legitimacy while on the move, delivering instant notifications and enhancing safety in the online recruiting environment

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