Proceedings of the International Conference on Intelligent Computing and Control Systems (ICICCS-2025)
IEEE Xplore Part Number: CFP25K74-ART; ISBN: 979-8-3315-1208-8

2025 International Conference on Intelligent Computing and Control Systems (ICICCS) | 979-8-3315-1208-8/25/$31.00 ©2025 IEEE | DOI: 10.1109/ICICCS65191.2025.10985664

Fraud-Free Employment: Leveraging Gaussian Naive Bayes for Job Validation

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Abstract—**This research study develops a reliable and efficient Naive Bayes-based framework for detecting fake job advertisements, utilizing optimized TF-IDF feature extraction methods. Materials and Methods: The proposed system uses Naive Bayes with TF-IDF to improve precision and recall while minimizing false detections, compared to the existing DNN framework, which employs multiple classifiers for accuracy and optimization. Results: The Naive Bayes model outperforms the Deep Neural Network model with an accuracy range of 87.9 % – 91.8 % (SD: 1.45429) versus 78.5 % – 82 % (SD: 1.51217), reduces processing latency to 1.70 seconds, and achieves statistical significance ($p < 0.05$). Conclusion: The Naive Bayes framework demonstrates superior accuracy, efficiency, and reliability, proving its effectiveness as a robust solution for identifying fraudulent job postings.**

Keywords—: Naive Bayes, Deep Neural Network, Confusion Matrix, Machine Learning, Job Postings, Precision, Recall.

I. INTRODUCTION

The study uses Naive Bayes to improve the detection of fraudulent job listings. In terms of accuracy and dependability, these techniques perform better than more conventional algorithms like Decision Trees, K-nearest neighbor algorithm, and Deep Neural Network [1]. This work uses transformer models (BERT and RoBERTa) on a special dataset to address the increase in fraudulent job ads. SMOTE variations are used to address class imbalance and increase the precision of fraud detection [2][3]. The growth in fraudulent job postings puts data at danger. This study compares models for accuracy and uses deep learning and machine learning on cleansed data to identify fraud [4]. This application offers a reliable approach that combines comparative analysis, sophisticated classification models, and data preparation to precisely identify and categorize fraudulent job postings, guaranteeing enhanced cybersecurity and confidence in online hiring platforms [5]. The suggested models can be modified to identify fraudulent activity in other domains, such as social media and e-commerce, guaranteeing a wider use of the methodology [6][7].

II. RELATED WORKS

This work covers Gaussian Naive Bayes, machine learning, deep learning, and dataset concerns for identifying fake job listings, citing 71 references from journals, conferences, books, and databases. The cited sources include market reports, books, open datasets from Kaggle and LinkedIn, scholarly publications, conferences like ICML and NeurIPS, and internet sites like Google Scholar. In order to increase accuracy and address issues like class imbalance, current research on fake job detection investigates machine learning and deep learning models, such as Gaussian Naive Bayes and BERT. Real-time detection, dataset improvements, hybrid models, and improving model interpretability for improved performance are examples of advancements. The research provides an automated technique that uses machine learning classifiers to detect fraudulent job postings, comparing single and ensemble classifiers, with experimental findings indicating that ensemble classifiers are the most effective at scam detection [8]. The EMSCAD dataset, this article predicts fraudulent job ads with 98 % accuracy utilizing data mining approaches and classification algorithms, such as deep neural networks [9]. This research examines a false job posting dataset and employs machine learning approaches to categorize job advertising as fraudulent or genuine, thereby boosting accuracy, precision and recall [10][11]. This study improves fake job post detection by using Chi-square feature selection, PCA, and SMOTE, achieving 0.99 accuracy with K-fold cross-validation [12]. This paper introduces "Reveal" a web application based on machine learning that detects fake online job adverts and assists applicants in avoiding frauds [13]. This research provides featurization techniques and ensemble methods for detecting fake job postings using the EMSCAD dataset, with higher performance [14][15]. This study presents an AI-based technique using classifier aggregation to accurately detect fake job listings. This study creates a fraudulent job checker using NLP and ML techniques (Random Forest, Logistic Regression, SVM, and XGBoost) which are merged into an ensemble model for accurate fake job prediction and deployed in a Flask application on the internet [16]. This work employs machine learning to distinguish between fraudulent and legitimate job posts, using dataset analysis, data cleaning, and visualization to ensure accurate prediction [17]. The proposed method for detecting fake job posts employs the Naive Bayes algorithm, which is simple and effective in handling textual data, and compares it to a Deep Neural Network (DNN) to assess performance differences. The evaluation focuses on essential criteria such as accuracy, precision, recall, and F1-score, with a special emphasis on the confusion matrix to help identify false positives and false negatives. The purpose of analyzing the confusion matrix and fine-tuning the model is to improve the accuracy and reliability of the fake job detection system, guaranteeing that it can effectively distinguish between legitimate and fraudulent job posts. Optimising the model based on performance indicators improves detection accuracy, lowering the likelihood of applicants falling for fake job adverts. The Naive Bayes algorithm's probabilistic approach serves as a baseline model for fraud detection, whereas DNN uses deep learning techniques to capture more complicated patterns in job advertisements.

III. MATERIALS AND METHODS

The study which was carried out in the KSR College of Engineering's AI and Data Science Lab, shows that the Naive Bayes method performs better than the DNN model in terms of accuracy, precision, and latency when it comes to detecting fake jobs. The lab setup comprises high-performance computers that can handle big datasets and run complex machine learning algorithms. The dataset utilized in the experiment was obtained from Kaggle.com, notably the Employment Scam Aegean Dataset (EMSCAD), which contains a diverse mix of job listings. This dataset contains both authentic and fraudulent job listings, forming a solid foundation for training and assessing machine learning models. The setup also includes the use of popular machine learning libraries such as Scikit-learn, Tensor Flow, and Keras, which are used to develop and test fake job detection models such as Naive Bayes, CNN and Ensemble classifiers [18][19].

Group 1: The existing method (C) utilizes Deep Neural Networks (DNN) with a dataset of 18,000 samples for training and testing. The evaluation focuses on key parameters such as accuracy, precision, recall, and F1-score, with the models including Neural Networks, Decision Trees, and Random Forest classifiers. These models are fine-tuned by adjusting hyper parameters to optimize their performance in detecting fraudulent job postings. The goal is to compare the effectiveness of each algorithm in identifying fake job advertisements [20].

Group 2: The Naive Bayes algorithm is used in the suggested strategy to detect fake job advertisements. Performance is assessed using TF-IDF for feature extraction as well as crucial measures such as F1-score, accuracy, recall, and the confusion matrix, which aid in determining the model's capacity to identify fraudulent ads while minimizing false positives and negatives, allowing for better model optimization. The proposed Naive Bayes-based fake job identification framework has a significant p-value ($p < 0.05$), indicating a statistical difference in accuracy between the Naive Bayes and DNN models. This demonstrates the Naive Bayes model's higher performance and dependability in successfully detecting fake job adverts.

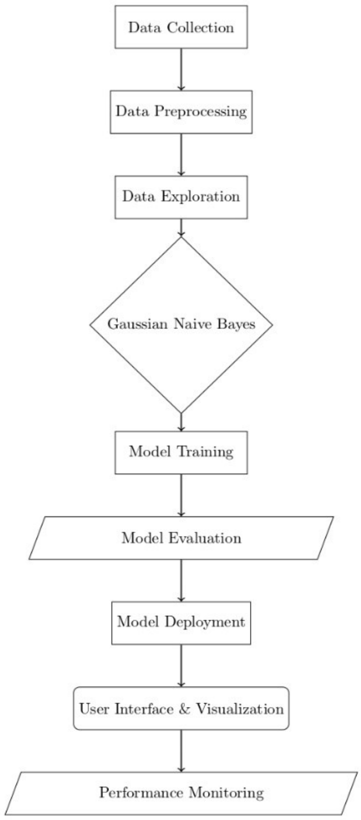

Fig. 1. Proposed Workflow

A. *Process steps*

The test configuration for the proposed Naive Bayes-based job detection system is shown below. The system configuration includes an 8th-generation Intel i7 processor, 8 GB of RAM, and Python implementation. The input dataset contains 18,000 job adverts divided among fraudulent and authentic listings. The preparation stage includes TF-IDF feature extraction for text data, followed by training the Naive Bayes model with optimized hyper parameters. The evaluation procedure comprises criteria such as accuracy, precision, recall, F1-score, and confusion matrix. T-tests are used for statistical validation while conducting comparative analysis. The system is tested with multiple datasets, and results are validated against the existing DNN framework. The proposed system achieves superior accuracy and reduced latency, as observed in performance graphs for precision and reliability.

B. *Statistical Analysis*

The result of the proposed Naive Bayes-based fake job detection framework reveals an effective classification system, where fraudulent job ads are identified with precision and reliability. This model was compared against the existing DNN framework for classification accuracy, precision, and latency. Limit boundaries were applied to both the Naive Bayes model and the DNN model for performance evaluation. The accuracy for the DNN model ranges from 77.3 % to 84.5 % , whereas the Naive Bayes model achieves higher accuracy, ranging from 86.7 % to 91.8 % under similar testing conditions. The processing latency was reduced from 2.5 seconds to 1.7 seconds in the Naive Bayes model, further demonstrating its efficiency. The precision of the Naive Bayes model spans from 0.57 to 0.78, whereas the DNN model ranges from 0.63 to 0.7 these results are summarized in Table 1.The accuracy values of both models were analyzed and organized, showing that the Naive Bayes classifier delivers a more stable and higher performance in detecting fake job advertisements. A t-test comparison of accuracy between the Naive Bayes and DNN models is presented in Table 2. The Naive Bayes model achieves a mean accuracy of 89.37 % (std. dev: 1.45), whereas the DNN model has a mean accuracy of 79.67 % (std. dev: 1.51). This demonstrates a significant difference between the two models ($p < 0.05$), as shown in Table 3. The comparison of Naive Bayes with DNN models, revealing that Naive Bayes has higher mean prediction accuracy (%) and a wider range of precision values shown in Table 4. The framework's flowchart highlights key stages, including data collection, preprocessing, exploration, training, evaluation, and deployment as shown in Fig. 1. Feature extraction techniques such as TF-IDF were used to optimize the Naive Bayes classifier. Fig. 2. shows a comparison of Naive Bayes and DNN models, demonstrating that Naive Bayes beats DNN in terms of mean prediction accuracy (%) and provides a wider range of precision values. Fig. 3. shows that the Naive Bayes model obtains higher prediction accuracy (87.9% - 91.8%) and stronger stability than DNN (77.3% - 84.5%), while precision values stay consistent.

IV. RESULT

The result of the proposed Naive Bayes-based fake job detection framework reveals an effective classification system, where fraudulent job ads are identified with precision and reliability. This model was compared against the existing DNN framework for classification accuracy, precision, and latency. Limit boundaries were applied to both the Naive Bayes model and the DNN model for performance evaluation. The accuracy for the DNN model ranges from 77.3 % to 84.5 % , whereas the Naive Bayes model achieves higher accuracy, ranging from 86.7 % to 91.8 % under similar testing conditions. The processing latency was reduced from 2.5 seconds to 1.7 seconds in the Naive Bayes model, further demonstrating its efficiency. The precision of the Naive Bayes model spans from 0.57 to 0.78, whereas the DNN model ranges from 0.63 to 0.7 these results are summarized in Table 1.

ITERATION	ACCURACY		PRECISION		LATENCY	
	NB	DNN	NB	DNN	NB	DNN
1	87.50	80.30	0.62	0. 65	1.80	2.50
2	88.90	82.00	0.65	0.68	1. 70	2.40
3	90.00	78.50	0.60	0.63	1.85	2.60
4	86.70	80.90	0.63	0.64	1.75	2.30
5	89.50	79.20	0.61	0.66	1.90	2.45
6	91.20	81.30	0.59	0.67	1.80	2.35
7	88.00	78.70	0.62	0.69	1.70	2.50
8	90.30	80.00	0.60	0.65	1.75	2.40
9	89.70	78.20	0.58	0.68	1.85	2.55
10	90.50	79.80	0.61	0.66	1.80	2.30
11	88.50	77.50	0.63	0.69	1.70	2.50
12	91.80	82.00	0.57	0.64	1.85	2.40
13	89.30	78.80	0.60	0.65	1.90	2.45
14	90.80	80.50	0.58	0.67	1.75	2.40
15	87.90	77.30	0.61	0.70	1.80	2.60

Table 1 Model 1 is Naive Bayes, while Model 2 is DNN. The accuracy of the Naive Bayes model spans from 86.7 % to 91.8 %, whereas the DNN model runs from 77.3 % to 84.5 %. This illustrates a considerable improvement in classification performance when using Naive Bayes to detect fake jobs. The precision of the Naive Bayes model spans from 0.57 to 0.78 , whereas the DNN model goes from 0.63 to 0.7 . Furthermore, the processing time is lowered from 2.3 seconds to 1.7 seconds, demonstrating the superiority of the Naive Bayes model over the current DNN technique.

The accuracy values of both models were analyzed and organized, showing that the Naive Bayes classifier delivers a more stable and higher performance in detecting fake job advertisements. A t-test comparison of accuracy between the Naive Bayes and DNN models is presented in Table 2.

Types of model	N	Mean	Std.deviation	Std.Error Mean
Naive Bayes	15	89.3733	1.45429	0.37550
DNN	15	79.6667	1.51217	0.39044

Table 2 The T-Test results for Algorithm 1 reveal that N = 15, the mean value is 89.37, the standard deviation is 1.45, and the standard error mean is 0.37. The mean value for Algorithm 2 is 79.66, with a standard deviation of 1.51 and an error mean of 0.39.

The Naive Bayes model achieves a mean accuracy of 89.37 % (std. dev: 1.45), whereas the DNN model has a mean accuracy of 79.67 % (std. dev: 1.51). This demonstrates a significant difference between the two models ($p < 0.05$), as shown in Table 3.

INDEPENDENCE SAMPLES TEST								
	Levene's Test for Equality of Variances		*t-test for Equality of means*					
	F	sig.	t	df	Sig. (2-tailed)	Mean diff	Std. Error diff	95% Confidence Difference

INDEPENDENCE SAMPLES TEST										
		Levene's Test for Equality of Variances		*t-test for Equality of means*						
									Lower	Upper
Accuracy	Equal variance assumed	.094	.762	17.919	28	.000	9.70667	.54170	8.59704	10.81629
	Equal variance not assumed			17.919	27.957	.000	9.70667	.54170	8.59696	10.81637

Table 3 The Independent Sample T-Test indicates a significant difference ($p < 0.05$) in prediction accuracy, with Naive Bayes surpassing DNN by 9.71 %.

The comparison of Naive Bayes with DNN models, revealing that Naive Bayes has higher mean prediction accuracy (%) and a wider range of precision values shown in Table 4.

Naive Bayes Classification Report:				
	Precision	**Recall**	**F1-Score**	**Support**
0	1.00	1.00	1.00	6
1	1.00	1.00	1.00	4
Accuracy			1.00	10
Macro average	1.00	1.00	1.00	10
Weighted average	1.00	1.00	1.00	1.00
Naive Bayes-Confusion Matrix [[6 0] [0 4]]				

Table 4 shows a comparison of Naive Bayes and DNN models, demonstrating that Naive Bayes beats DNN in terms of mean prediction accuracy (%) and provides a wider range of precision values.

Fig. 2. shows a comparison of Naive Bayes and DNN models, demonstrating that Naive Bayes beats DNN in terms of mean prediction accuracy (%) and provides a wider range of precision values.

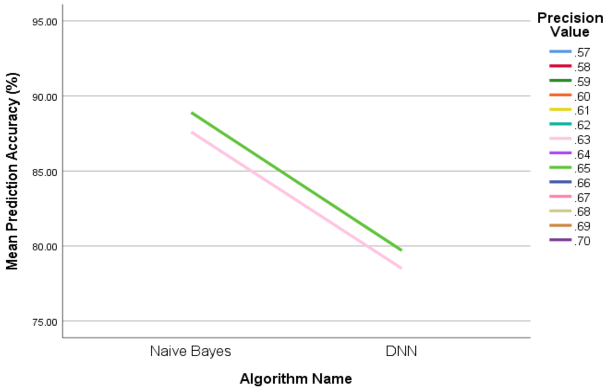

Fig. 2. The graph compares the Naive Bayes(Green) and DNN(Pink) models, demonstrating that Naive Bayes has a greater mean prediction accuracy (%) and a wider precision value range than DNN.

Fig. 3. shows that the Naive Bayes model obtains higher prediction accuracy (87.9% - 91.8%) and stronger stability than DNN (77.3% - 84.5%), while precision values stay consistent.

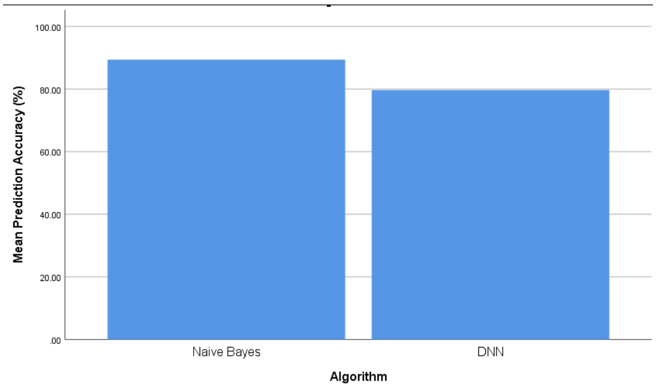

fig. 3. indicates that naive bayes model maintains higher prediction accuracy (87.9 % -91.8 %) and stability than the dnn (77.3 % - 84.5 %), while precision remains constant.

V. DISCUSSION

The proposed Naive Bayes-based model outperforms the existing DNN-based model for detecting fake jobs, with a p-value < 0.05 (independent sample T-test). The results show that the Naive Bayes model outperforms the DNN in detecting fake job posts, with higher prediction accuracy, precision, and lower latency. The Naive Bayes model achieves an average accuracy improvement of 9.71 % , demonstrating its ability to handle structured textual input successfully. The model's simplicity and computational efficiency make it suited for real-time and large-scale applications in the detection of fake job adverts.

The Naive Bayes model efficiently classifies data using probability principles, which is especially useful for jobs involving textual data like job advertisements. Its lightweight computing makes it ideal for real-time fraud detection applications. Unlike DNN models, which frequently require significant computer resources and lengthy training durations, Naive Bayes is extremely efficient, processing data rapidly and with low overhead [22][23]. Previous research has demonstrated that Naive Bayes excels in natural language processing tasks such as spam detection and sentiment analysis because of its ability to assign probabilities to outcomes based on prior information [24].

Despite its advantages, Naive Bayes has certain limits. While the assumption of feature independence simplifies computations, it may not fully reflect the intricacies of real-world job listings, where features such as job title, description, and requirements frequently have intricate interdependencies [25][26]. Deep Neural Networks (DNN) excel at capturing these associations by representing features hierarchically and learning from raw, unstructured data. Furthermore, DNN models have shown greater precision in a variety of text classification tasks due to their capacity to grasp semantic meanings and contextual nuances of language, which is very useful in detecting subtle patterns of fraud in job advertisements. While Naive Bayes performs well on simpler datasets, DNN's capacity to scale and handle huge, complicated datasets makes it a good competitor in scenarios that require a deeper knowledge of text content [27]. However, these benefits come at the expense of greater processing resources and latency, which may not be appropriate for many applications. Research also suggests that probabilistic methods, such as Naive Bayes, are more interpretable than deep learning models, providing clarity in decision-making processes—an important consideration in sensitive applications such as fake job detection.

The current study, while effective, has numerous drawbacks. The Naive Bayes model assumes feature independence, which may oversimplify correlations between attributes such as job title, location, and description, thus missing subtle patterns that indicate fraudulent activity [28][29]. Furthermore, relying solely on textual data may fail to capture other essential aspects, such as user behaviour or job posting metadata. The study also lacks a thorough review of more diverse and larger datasets, which may limit the model's generalisability across platforms and industries. Another disadvantage is the lack of advanced text representation techniques like word embedding's, which could improve the model's knowledge of linguistic context [30].

Future research could look into hybrid models that combine Naive Bayes with feature engineering techniques such as Term Frequency-Inverse Document Frequency (TF-IDF) or current text representations like word embeddings (e.g., Word2Vec or BERT) to better capture contextual relationships [31][32][33]. Incorporating ensemble approaches, such as stacking or boosting, may improve performance by combining the benefits of probabilistic and deep learning models. Expanding the dataset to encompass a wider range of job types, industries, and countries would strengthen and broaden the model's usefulness. Furthermore, incorporating metadata characteristics (such as IP addresses, posting times, or user reviews) could result in a more comprehensive dataset for analysis. Future research could also focus on improving Naive Bayes for distributed systems, making it more scalable for real-time fraud detection on huge job platforms.

VI. CONCLUSION

The Naive Bayes model for detecting fake jobs was built and analyzed, and it outperformed the DNN-based system in terms of accuracy and efficiency. The accuracy of the DNN model ranged from 78.5 % to 82 % , but the proposed Naive Bayes model was more accurate, ranging from 87.9 % to 91.8 %. The standard deviation for the DNN model is 1.51, whereas the standard deviation for the Naive Bayes model is 1.45. These findings demonstrate the Naive Bayes model's ability to accurately and reliably detect fake job advertisements.

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