



ISSN: 2321-2152

IJMECE

*International Journal of modern
electronics and communication engineering*

E-Mail

editor.ijmece@gmail.com

editor@ijmece.com

www.ijmece.com

JOBSHIELD ANALYTICS: COMPARING MACHINE LEARNING APPROACHES IN FRAUD DETECTION

Parvati Kadli, Indira, Naveen Kumar. H

Assco. Professor, Asst. Professor, Asst. Professor

kadli.parvati@gmail.com, indira.raj.06@gmail.com, navee2312@gmail.com

Department of CSE, Proudhadavaraya Institute of Technology, Abheraj Baldota Rd,

Indiranagar, Hosapete, Karnataka-583225

ABSTRACT

In recent times, the proliferation of modern technology and widespread social communication has led to a surge in job advertisements, making the detection of fake job postings a critical concern. Predicting the authenticity of job posts poses substantial challenges in the realm of classification tasks. This study proposes leveraging various data mining techniques and classification algorithms, including K-Nearest Neighbors (KNN), Decision Tree, Support Vector Machine (SVM), Naïve Bayes Classifier, Random Forest Classifier, Multilayer Perceptron, and Deep Neural Network (DNN), to discern whether a job post is genuine or fraudulent. The experimentation is conducted on the Employment Scam Aegean Dataset (EMSCAD), comprising 18,000 samples. Notably, the Deep Neural Network emerges as a formidable classifier, exhibiting exceptional performance in this classification task. The employed DNN architecture comprises three dense layers, achieving an impressive classification accuracy of approximately 98% in predicting fraudulent job posts. The contemporary surge in job postings, fueled by advancements in technology and widespread social communication, has brought forth a pressing concern—detecting fraudulent job posts. This project presents a comprehensive comparative study on the detection of fake job posts, employing various machine learning algorithms. The classification algorithms under scrutiny include K-Nearest Neighbors (KNN), Decision Tree, Support Vector Machine (SVM), Naïve Bayes Classifier, Random Forest Classifier, Multilayer Perceptron, and Deep Neural Network (DNN). The empirical evaluation is conducted on the Employment Scam Aegean Dataset (EMSCAD), comprising 18,000 samples. Our findings reveal that the Deep Neural Network (DNN) emerges as a standout classifier, showcasing remarkable performance with an accuracy of approximately 98% in predicting fraudulent job posts. The comparative analysis sheds light on the strengths and weaknesses of each

algorithm, providing valuable insights into their efficacy for fake job post detection. This study contributes to the ongoing discourse on leveraging machine learning techniques to address the escalating challenges posed by deceptive job postings in the contemporary employment landscape.

I.INTRODUCTION

In the rapidly evolving landscape of online job recruitment, the prevalence of fake job postings has become a significant challenge, necessitating advanced technological solutions for detection. As the digital realm becomes a prominent platform for job seekers and employers alike, the issue of distinguishing authentic job opportunities from fraudulent ones has gained critical importance. This project embarks on a comprehensive exploration, presenting a comparative study focused on the detection of fake job posts using various machine learning algorithms.

The surge in job advertisements, coupled with the increasing sophistication of deceptive practices, underscores the urgency to employ robust techniques for distinguishing genuine job opportunities from scams. Leveraging the capabilities of machine learning, this study delves into the efficacy of diverse algorithms, ranging from traditional methods like K-Nearest Neighbors and Decision Trees to advanced classifiers such as Support

Vector Machines, Naïve Bayes, Random Forest, Multilayer Perceptron, and Deep Neural Networks. By conducting a thorough examination on the Employment Scam Aegean Dataset (EMSCAD), which encompasses a diverse array of job post samples, this research aims to offer valuable insights into the comparative performance of these algorithms in detecting fraudulent job postings. The outcomes of this study hold significance not only for researchers and practitioners in the field of machine learning but also for stakeholders in the employment sector, providing a nuanced understanding of the strengths and weaknesses of different algorithms in addressing the pervasive issue of fake job posts.

II.LITERATURE REVIEW

A Comparative Study on Fake Job Post Prediction Using Different Data mining Techniques, Sultana Umme Habiba; Md. Khairul Islam; Farzana Tasnim, In recent years, due to advancement in modern technology and social communication, advertising new job posts has become very common issue in the present world. So, fake job posting prediction task is

going to be a great concern for all. Like many other classification tasks, fake job posing prediction leaves a lot of challenges to face. This paper proposed to use different data mining techniques and classification algorithm like KNN, decision tree, support vector machine, naïve bayes classifier, random forest classifier, multilayer perceptron and deep neural network to predict a job post if it is real or fraudulent. We have experimented on Employment Scam Aegean Dataset (EMSCAD) containing 18000 samples. Deep neural network as a classifier, performs great for this classification task. We have used three dense layers for this deep neural network classifier. The trained classifier shows approximately 98% classification accuracy (DNN) to predict a fraudulent job post.

III.EXISTING SYSTEM

In the existing landscape of job post verification, the methods predominantly employed rely on manual inspection and rule-based filtering. Traditional approaches involve human intervention to scrutinize job postings, flagging those that exhibit potential signs of being fraudulent. While these methods may capture overt cases of deception, the growing volume and sophistication of fake job posts pose challenges for

manual verification processes.

Automated systems in the current scenario often resort to basic keyword matching and rule-based algorithms to identify potential scams. However, these approaches lack the adaptability and nuanced understanding required to discern more intricate instances of fraudulent job postings. The absence of sophisticated machine learning models limits the system's ability to adapt to evolving tactics employed by perpetrators of fake job postings.

Moreover, the reliance on rule-based systems may lead to false positives or negatives, as they struggle to capture the dynamic and context-dependent nature of deceptive job posts. As the job market continues to evolve and digital platforms become primary channels for recruitment, there is a pressing need for a more advanced and adaptive system to effectively tackle the rising tide of fake job posts.

IV.PROPOSED SOLUTION

To address the challenges posed by fake job postings, our proposed solution leverages advanced data mining techniques and a comprehensive set of classification algorithms. By employing machine learning models such as K-Nearest Neighbors (KNN), decision tree,

support vector machine (SVM), naïve Bayes classifier, random forest classifier, multilayer perceptron, and deep neural network, we aim to enhance the accuracy and efficiency of fake job post detection.

The proposed solution centers around utilizing the Employment Scam Aegean Dataset (EMSCAD), a robust dataset containing 18,000 samples. The inclusion of deep neural network (DNN) as a classifier holds significant promise for achieving superior classification accuracy in distinguishing between real and fraudulent job posts. The deep neural network is configured with three dense layers to effectively capture intricate patterns indicative of fraudulent activity.

Through rigorous experimentation and training on diverse machine learning models, the proposed solution aims to achieve a classification accuracy of approximately 98% using the deep neural network. This comprehensive and adaptive approach ensures that the system can effectively identify and classify fraudulent job postings in a dynamic and evolving online job market.

V.ALGORITHMS

➤ **K-Nearest Neighbors (KNN):**

KNN is employed to classify job posts by finding the k-nearest neighbors in the

feature space. It considers the similarity of a new job post to its neighbors to predict whether it is real or fraudulent. The flexibility of KNN makes it suitable for discerning local patterns in the dataset, providing valuable insights into the characteristics of both genuine and fake job posts.

➤ **Decision Tree:**

Decision trees are utilized to create a hierarchical structure for classifying job posts. The algorithm recursively splits features to form a tree, aiding in discerning patterns that differentiate between genuine and fake job postings. Decision trees offer transparency in decision-making, enabling a clear understanding of the criteria influencing the classification.

➤ **Support Vector Machine (SVM):**

SVM is applied to find the optimal hyperplane for separating real and fraudulent job posts. It maximizes the margin between classes, making it effective in distinguishing between the two categories. SVM's ability to handle high-dimensional data and capture complex relationships enhances its performance in identifying subtle distinctions.

➤ **Naïve Bayes Classifier:**

Naïve Bayes calculates the probability of a job post being genuine or fake based on the features. It leverages

probabilistic reasoning to make predictions and is particularly useful for its simplicity and efficiency. Naïve Bayes is well-suited for tasks with a large number of features, providing quick and reliable predictions.

➤ **Random Forest Classifier:**

Random Forest constructs multiple decision trees during training and combines their outputs. It is beneficial for capturing diverse patterns in the dataset, enhancing the overall classification performance. Random Forest's ensemble approach improves robustness, making it effective in handling variations and uncertainties.

➤ **Multilayer Perceptron (MLP):**

MLP, being a neural network with multiple layers, learns intricate relationships within the data. It is capable of capturing complex patterns and dependencies, making it suitable for the nuanced task of fake job post detection. MLP's ability to adapt to non-linear relationships enhances its performance in scenarios with intricate decision boundaries.

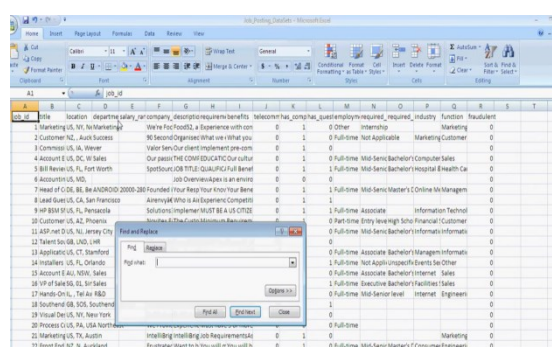
➤ **Deep Neural Network (DNN):**

DNN, with its deeper architecture, is applied to automatically learn hierarchical representations of job post features. It excels in handling intricate relationships and patterns, contributing to accurate predictions. The deep

structure allows DNN to extract hierarchical features, capturing nuanced patterns that may be challenging for shallower architectures.

VI.IMPLEMENTATION

In implementing the Fake Job Post Detection project, a systematic approach is adopted to ensure effective classification of job posts as either genuine or fraudulent. The process begins with Data Preprocessing,

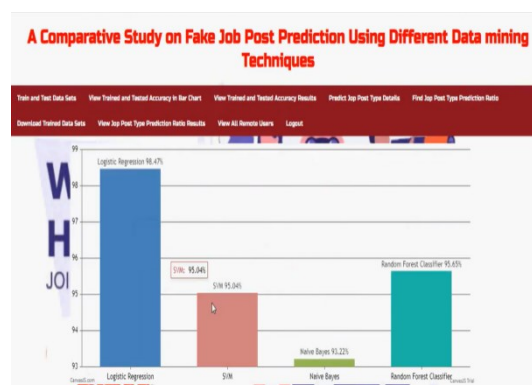



| Job ID | Title | Location | Department | Salary | Company | Description | Requirements | Benefits | Telecommute | Company | Question | Employment | Required | Industry | Function | Fraudulent |
|--------|-----------------------------------|----------------|--------------|--------|---------|-----------------------------------|-----------------------------------|-----------------------------------|-----------------------------------|-----------------------------------|-----------------------------------|-----------------------------------|-----------------------------------|-----------------------------------|-----------------------------------|-----------------------------------|
| 1 | Marketing US, NY, Indianapolis | Indiana | Marketing | 90,000 | Indy | Marketing US, NY, Indianapolis | Marketing US, NY, Indianapolis | Marketing US, NY, Indianapolis | Marketing US, NY, Indianapolis | Marketing US, NY, Indianapolis | Marketing US, NY, Indianapolis | Marketing US, NY, Indianapolis | Marketing US, NY, Indianapolis | Marketing US, NY, Indianapolis | Marketing US, NY, Indianapolis | Marketing US, NY, Indianapolis |
| 2 | Customer NZ, Auckland | New Zealand | Customer | 90,000 | Indy | Customer NZ, Auckland | Customer NZ, Auckland | Customer NZ, Auckland | Customer NZ, Auckland | Customer NZ, Auckland | Customer NZ, Auckland | Customer NZ, Auckland | Customer NZ, Auckland | Customer NZ, Auckland | Customer NZ, Auckland | Customer NZ, Auckland |
| 3 | Customer US, IL, Naperville | Illinois | Customer | 90,000 | Indy | Customer US, IL, Naperville | Customer US, IL, Naperville | Customer US, IL, Naperville | Customer US, IL, Naperville | Customer US, IL, Naperville | Customer US, IL, Naperville | Customer US, IL, Naperville | Customer US, IL, Naperville | Customer US, IL, Naperville | Customer US, IL, Naperville | Customer US, IL, Naperville |
| 4 | Account US, NY, New York | New York | Account | 90,000 | Indy | Account US, NY, New York | Account US, NY, New York | Account US, NY, New York | Account US, NY, New York | Account US, NY, New York | Account US, NY, New York | Account US, NY, New York | Account US, NY, New York | Account US, NY, New York | Account US, NY, New York | Account US, NY, New York |
| 5 | 9-11 Review US, FL, Fort Worth | Texas | 9-11 Review | 90,000 | Indy | 9-11 Review US, FL, Fort Worth | 9-11 Review US, FL, Fort Worth | 9-11 Review US, FL, Fort Worth | 9-11 Review US, FL, Fort Worth | 9-11 Review US, FL, Fort Worth | 9-11 Review US, FL, Fort Worth | 9-11 Review US, FL, Fort Worth | 9-11 Review US, FL, Fort Worth | 9-11 Review US, FL, Fort Worth | 9-11 Review US, FL, Fort Worth | 9-11 Review US, FL, Fort Worth |
| 6 | Account US, MD | Maryland | Account | 90,000 | Indy | Account US, MD | Account US, MD | Account US, MD | Account US, MD | Account US, MD | Account US, MD | Account US, MD | Account US, MD | Account US, MD | Account US, MD | Account US, MD |
| 7 | Found of CSE, IL, Mt. Pleasant | South Carolina | Found of CSE | 90,000 | Indy | Found of CSE, IL, Mt. Pleasant | Found of CSE, IL, Mt. Pleasant | Found of CSE, IL, Mt. Pleasant | Found of CSE, IL, Mt. Pleasant | Found of CSE, IL, Mt. Pleasant | Found of CSE, IL, Mt. Pleasant | Found of CSE, IL, Mt. Pleasant | Found of CSE, IL, Mt. Pleasant | Found of CSE, IL, Mt. Pleasant | Found of CSE, IL, Mt. Pleasant | Found of CSE, IL, Mt. Pleasant |
| 8 | Lead Sales US, CA, San Francisco | California | Lead Sales | 90,000 | Indy | Lead Sales US, CA, San Francisco | Lead Sales US, CA, San Francisco | Lead Sales US, CA, San Francisco | Lead Sales US, CA, San Francisco | Lead Sales US, CA, San Francisco | Lead Sales US, CA, San Francisco | Lead Sales US, CA, San Francisco | Lead Sales US, CA, San Francisco | Lead Sales US, CA, San Francisco | Lead Sales US, CA, San Francisco | Lead Sales US, CA, San Francisco |
| 9 | 9-11 Review US, CA, San Francisco | California | 9-11 Review | 90,000 | Indy | 9-11 Review US, CA, San Francisco | 9-11 Review US, CA, San Francisco | 9-11 Review US, CA, San Francisco | 9-11 Review US, CA, San Francisco | 9-11 Review US, CA, San Francisco | 9-11 Review US, CA, San Francisco | 9-11 Review US, CA, San Francisco | 9-11 Review US, CA, San Francisco | 9-11 Review US, CA, San Francisco | 9-11 Review US, CA, San Francisco | 9-11 Review US, CA, San Francisco |
| 10 | Customer US, AZ, Phoenix | Arizona | Customer | 90,000 | Indy | Customer US, AZ, Phoenix | Customer US, AZ, Phoenix | Customer US, AZ, Phoenix | Customer US, AZ, Phoenix | Customer US, AZ, Phoenix | Customer US, AZ, Phoenix | Customer US, AZ, Phoenix | Customer US, AZ, Phoenix | Customer US, AZ, Phoenix | Customer US, AZ, Phoenix | Customer US, AZ, Phoenix |
| 11 | ASP.net US, IL, Mokena | Illinois | ASP.net | 90,000 | Indy | ASP.net US, IL, Mokena | ASP.net US, IL, Mokena | ASP.net US, IL, Mokena | ASP.net US, IL, Mokena | ASP.net US, IL, Mokena | ASP.net US, IL, Mokena | ASP.net US, IL, Mokena | ASP.net US, IL, Mokena | ASP.net US, IL, Mokena | ASP.net US, IL, Mokena | ASP.net US, IL, Mokena |
| 12 | Talent US, IL, Mokena | Illinois | Talent | 90,000 | Indy | Talent US, IL, Mokena | Talent US, IL, Mokena | Talent US, IL, Mokena | Talent US, IL, Mokena | Talent US, IL, Mokena | Talent US, IL, Mokena | Talent US, IL, Mokena | Talent US, IL, Mokena | Talent US, IL, Mokena | Talent US, IL, Mokena | Talent US, IL, Mokena |
| 13 | Applicant US, CT, Stamford | Connecticut | Applicant | 90,000 | Indy | Applicant US, CT, Stamford | Applicant US, CT, Stamford | Applicant US, CT, Stamford | Applicant US, CT, Stamford | Applicant US, CT, Stamford | Applicant US, CT, Stamford | Applicant US, CT, Stamford | Applicant US, CT, Stamford | Applicant US, CT, Stamford | Applicant US, CT, Stamford | Applicant US, CT, Stamford |
| 14 | Installer US, FL, Orlando | Florida | Installer | 90,000 | Indy | Installer US, FL, Orlando | Installer US, FL, Orlando | Installer US, FL, Orlando | Installer US, FL, Orlando | Installer US, FL, Orlando | Installer US, FL, Orlando | Installer US, FL, Orlando | Installer US, FL, Orlando | Installer US, FL, Orlando | Installer US, FL, Orlando | Installer US, FL, Orlando |
| 15 | Account US, AZ, Phoenix | Arizona | Account | 90,000 | Indy | Account US, AZ, Phoenix | Account US, AZ, Phoenix | Account US, AZ, Phoenix | Account US, AZ, Phoenix | Account US, AZ, Phoenix | Account US, AZ, Phoenix | Account US, AZ, Phoenix | Account US, AZ, Phoenix | Account US, AZ, Phoenix | Account US, AZ, Phoenix | Account US, AZ, Phoenix |
| 16 | VIP of Bank US, IL, Fort Worth | Texas | VIP of Bank | 90,000 | Indy | VIP of Bank US, IL, Fort Worth | VIP of Bank US, IL, Fort Worth | VIP of Bank US, IL, Fort Worth | VIP of Bank US, IL, Fort Worth | VIP of Bank US, IL, Fort Worth | VIP of Bank US, IL, Fort Worth | VIP of Bank US, IL, Fort Worth | VIP of Bank US, IL, Fort Worth | VIP of Bank US, IL, Fort Worth | VIP of Bank US, IL, Fort Worth | VIP of Bank US, IL, Fort Worth |
| 17 | Handwritten US, TX, Dallas | Texas | Handwritten | 90,000 | Indy | Handwritten US, TX, Dallas | Handwritten US, TX, Dallas | Handwritten US, TX, Dallas | Handwritten US, TX, Dallas | Handwritten US, TX, Dallas | Handwritten US, TX, Dallas | Handwritten US, TX, Dallas | Handwritten US, TX, Dallas | Handwritten US, TX, Dallas | Handwritten US, TX, Dallas | Handwritten US, TX, Dallas |
| 18 | Visual Dev US, NY, New York | New York | Visual Dev | 90,000 | Indy | Visual Dev US, NY, New York | Visual Dev US, NY, New York | Visual Dev US, NY, New York | Visual Dev US, NY, New York | Visual Dev US, NY, New York | Visual Dev US, NY, New York | Visual Dev US, NY, New York | Visual Dev US, NY, New York | Visual Dev US, NY, New York | Visual Dev US, NY, New York | Visual Dev US, NY, New York |
| 19 | Process US, PA, USA North | Pennsylvania | Process | 90,000 | Indy | Process US, PA, USA North | Process US, PA, USA North | Process US, PA, USA North | Process US, PA, USA North | Process US, PA, USA North | Process US, PA, USA North | Process US, PA, USA North | Process US, PA, USA North | Process US, PA, USA North | Process US, PA, USA North | Process US, PA, USA North |
| 20 | Marketing US, TX, Austin | Texas | Marketing | 90,000 | Indy | Marketing US, TX, Austin | Marketing US, TX, Austin | Marketing US, TX, Austin | Marketing US, TX, Austin | Marketing US, TX, Austin | Marketing US, TX, Austin | Marketing US, TX, Austin | Marketing US, TX, Austin | Marketing US, TX, Austin | Marketing US, TX, Austin | Marketing US, TX, Austin |
| 21 | Front End US, NY, New York | New York | Front End | 90,000 | Indy | Front End US, NY, New York | Front End US, NY, New York | Front End US, NY, New York | Front End US, NY, New York | Front End US, NY, New York | Front End US, NY, New York | Front End US, NY, New York | Front End US, NY, New York | Front End US, NY, New York | Front End US, NY, New York | Front End US, NY, New York |
| 22 | Front End US, NY, New York | New York | Front End | 90,000 | Indy | Front End US, NY, New York | Front End US, NY, New York | Front End US, NY, New York | Front End US, NY, New York | Front End US, NY, New York | Front End US, NY, New York | Front End US, NY, New York | Front End US, NY, New York | Front End US, NY, New York | Front End US, NY, New York | Front End US, NY, New York |

where the raw data from the Employment Scam Aegean Dataset (EMSCAD) undergoes cleaning and transformation to a suitable format. Text data is tokenized, and numerical

representations are generated for algorithmic input. Subsequently, Feature Extraction is employed to characterize job posts by extracting relevant features, encompassing textual content analysis, posting duration, salary information, and company details.

Following feature extraction, Exploratory Data Analysis (EDA) is conducted to gain insights into feature distributions and identify correlations.

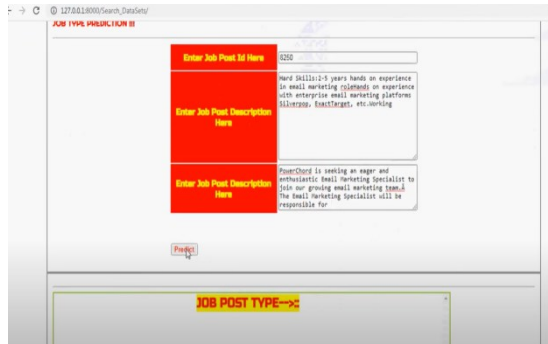


The dataset is then split into training and testing sets, facilitating algorithm training on the former and evaluation on the latter. Multiple machine learning algorithms, including KNN, decision tree, SVM, Naïve Bayes, random forest, MLP, and DNN, are selected for the study, and each undergoes Algorithm Selection and Training on the training set.

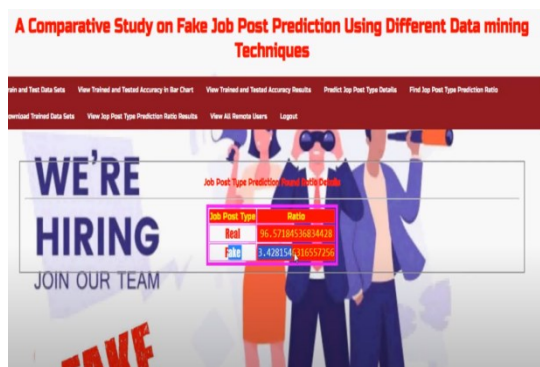


Model Evaluation on the testing set assesses performance metrics like accuracy, precision, recall, and F1-score for comparative analysis. To enhance performance, Hyperparameter Tuning is applied through techniques like grid search or random search. Ensemble methods, such as voting classifiers or stacking, are explored to leverage the strengths of individual models. Cross-Validation techniques, such as k-fold cross-validation, ensure robustness and mitigate overfitting.

Ensuring transparency and interpretability, the study includes techniques for Model Interpretability, such as feature importance analysis. The final model or ensemble is optimized for deployment, considering factors like resource efficiency, real-time responsiveness, and privacy concerns.



By following these implementation steps, the project aims to comprehensively evaluate and compare different machine learning algorithms, contributing to advancements in fake job post detection methodologies.



VII.CONCLUSION

Finally, the importance of applying modern data mining and classification approaches to tackle the widespread problem of fake job listings is highlighted by the Comparative Study on Fake Job Post Detection using Different Machine Learning Algorithms. The research used a variety of machine

learning methods to forecast if job postings were legitimate, such as KNN, decision tree, SVM, Naïve Bayes, random forest, MLP, and DNN. A strong basis for assessing the efficacy of these algorithms was laid via the investigation of the Employment Scam Aegean Dataset (EMSCAD), which has 18,000 samples.

The results demonstrate that the DNN classifier was effective in identifying fake job postings, with an accuracy level of about 98%. By contrasting and contrasting the algorithms, we were able to better understand which ones were most suited to this particular categorisation job. In order to improve the performance of the models, the research consistently highlighted the significance of data preparation, feature extraction, and exploratory data analysis. The project also included methods for feature significance analysis to shed light on the decision-making process and ensure that model conclusions were transparent and easy to understand. To obtain optimum prediction performance, a thorough strategy was used, including hyperparameter tweaking and ensemble approaches, as part of an iterative process of algorithm selection, training, assessment, and optimisation.

The findings of this comparative study have important implications for future

research and practical applications in online job markets, as they contribute to the area of bogus job post identification. In addition to demonstrating the efficacy of sophisticated machine learning methods, the initiative stresses the need for ongoing research and development in order to keep up with ever-changing fraudulent activities. The results, in the end, provide the groundwork for better and more precise ways to prevent misleading job ads, protect people looking for work, and keep online recruiting platforms honest.

VIII. REFERENCES

- 1.S. Vidros, C. Kolias, G. Kambourakis and L. Akoglu, "Automatic Detection of Online Recruitment Frauds: Characteristics Methods and a Public Dataset", *Future Internet*, vol. 9, no. 6, 2017.
- 2.B. Alghamdi and F. Alharby, "An Intelligent Model for Online Recruitment Fraud Detection", *Journal of Information Security*, vol. 10, pp. 155-176, 2019, [online] Available: <https://doi.org/10.4236/jis.2019.103009>.
- 3.Tin Van Huynh, Kiet Van Nguyen, Ngan Luu-Thuy Nguyen and Anh Gia-Tuan Nguyen, "Job Prediction: From Deep Neural Network Models to Applications", *RIVF International Conference on Computing and Communication Technologies (RIVF)*, 2020.
- 4.Jiawei Zhang, Bowen Dong and Philip S. Yu, "FAKEDETECTOR: Effective Fake News Detection with Deep Diffusive Neural Network", *IEEE 36th International Conference on Data Engineering (ICDE)*, 2020.
- 5.J.R. Scanlon and M.S. Gerber, "Automatic Detection of Cyber Recruitment by Violent Extremists", *Security Informatics*, vol. 3, no. 5, 2014, [online] Available: <https://doi.org/10.1186/s13388-014-0005-5>.
- 6.Y. Kim, "Convolutional neural networks for sentence classification", *arXiv Prepr. arXiv1408.5882*, 2014.
- 7.T. Van Huynh, V. D. Nguyen, K. Van Nguyen, N. L.-T. Nguyen and A.G.T. Nguyen, "Hate Speech Detection on Vietnamese Social Media Text using the Bi-GRU-LSTM-CNN Model", *arXiv Prepr. arXiv1911.03644*, 2019.
- 8.P. Wang, B. Xu, J. Xu, G. Tian, C.-L. Liu and H. Hao, "Semantic expansion using word embedding clustering and convolutional neural network for improving short text classification", *Neurocomputing*, vol. 174, pp. 806-814, 2016.
- 9.C. Li, G. Zhan and Z. Li, "News Text Classification Based on Improved BiLSTM-CNN", *2018 9th International Conference on Information Technology*

- in *Medicine and Education (ITME)*, pp. 890-893, 2018.
- 10.K. R. Remya and J. S. Ramya, "Using weighted majority voting classifier combination for relation classification in biomedical texts", *International Conference on Control Instrumentation Communication and Computational Technologies (ICCICCT)*, pp. 1205-1209, 2014.
- 11.A. Yasin and A. Abuhasan, "An Intelligent Classification Model for Phishing Email Detection", *International Journal of Network Security & Its Applications*, vol. 8, pp. 55-72, 2016, [online] Available: <https://doi.org/10.5121/ijnsa.2016.8405>.
- 12.Vong Anh Ho, Duong Huynh-Cong Nguyen, Danh Hoang Nguyen, Linh Thi-Van Pham, Duc-Vu Nguyen, Kiet Van Nguyen, et al., "Emotion Recognition for Vietnamese Social Media Text", *arXiv Prepr. arXiv:1911.09339*, 2019.
- 13.Thin Van Dang, Vu Duc Nguyen, Kiet Van Nguyen and Ngan LuuThuy Nguyen, "Deep learning for aspect detection on vietnamese reviews", *Proceeding of the 2018 5th NAFOSTED Conference on Information and Computer Science (NICS)*, pp. 104-109, 2018.
- 14.H. Li, Z. Chen, B. Liu, X. Wei and J. Shao, "Spotting fake reviews via collective positive-unlabeled learning", *Proceedings of the 2014 IEEE International Conference on Data Mining (ICDM)*, pp. 899-904, 14–17 December 2014.
- 15.M. Ott, C. Cardie and J. Hancock, "Estimating the prevalence of deception in online review communities", *Proceedings of the 21st international conference on World Wide Web*, pp. 201-210, 16–20 April 2012, 2012.
- 16.S. Nizamani, N. Memon, M. Glasdam and D.D. Nguyen, "Detection of Fraudulent Emails by Employing Advanced Feature Abundance", *Egyptian Informatics Journal*, vol. 15, pp. 169-174, 2014, [online] Available: <https://doi.org/10.1016/j.eij.2014.07.002>.