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Fake/Real Job Posting Detection Using Machine Learning

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Abstract: The rise of online job platforms has been accompanied by an increasing number of fraudulent job postings, posing significant risks to job seekers in terms of privacy, financial security, and mental well-being. This paper presents an AI-powered Fake Job Detection system designed to automatically distinguish between genuine and fraudulent job postings using a supervised machine learning approach. We employ the publicly available fake_job_postings.csv dataset, which contains both structured and unstructured data, including job titles, locations, descriptions, and company profiles. After extensive preprocessing—such as text cleaning, feature extraction using TF-IDF for unstructured data, and handling missing values—we trained and evaluated multiple classification models, including Random Forest, Support Vector Machine (SVM), Logistic Regression, and XGBoost. Additionally, we implemented an ensemble Voting Classifier to leverage the strengths of individual models. Among these, the Random Forest Classifier demonstrated the highest performance in terms of accuracy, precision, recall, and F1-score. The final system provides a 'fakeness score' by computing the prediction probability, offering users a clear and interpretable output. Furthermore, we developed a web-based interface that enables users to input job postings and receive real-time predictions on their legitimacy. Our system not only improves trust in online recruitment but also offers a scalable solution to combat job fraud using AI and natural language processing. The results highlight the potential of machine learning in mitigating online employment scams and provide a foundation for future enhancements, such as multilingual support and adaptive learning based on evolving fraud patterns.
Keywords: Fake Job Detection, Machine Learning, Natural Language Processing, Random Forest Classifier, Supervised Learning, TF-IDF, Ensemble Learning, Online Recruitment, Text Classification, Web-based Application.

I. INTRODUCTION

In the digital age, online job portals have revolutionized the recruitment process by bridging the gap between employers and job seekers across the globe. Platforms such as LinkedIn, Indeed, and Glassdoor have made it easier than ever to apply for jobs with just a few clicks. However, this accessibility has also introduced a significant downside: the proliferation of fake or fraudulent job postings. These postings often appear legitimate but are carefully crafted to deceive job seekers, leading to financial scams, data theft, or even phishing attacks. The consequences of falling prey to such fraud can be devastating, especially for fresh graduates or individuals urgently seeking employment.

Despite efforts by online platforms to manually verify postings or implement basic filters, the sheer volume and complexity of job data make manual detection inefficient, inconsistent, and prone to error. This growing issue demands an automated, intelligent solution that can accurately distinguish between genuine and fraudulent job listings using advanced machine learning (ML) and natural language processing (NLP) techniques. In this study, we propose a comprehensive Fake Job Detection system that leverages supervised machine learning to classify job postings as real or fake. The system is trained using the publicly available fake_job_postings.csv dataset, which contains a mix of structured features (such as title, location, salary range, and telecommuting status) and unstructured textual content (such as job descriptions, requirements, and company profiles). To prepare the data for analysis, we performed extensive preprocessing including data cleaning, null value imputation, label encoding, and text normalization. For unstructured data, we applied NLP techniques such as tokenization, stop-word removal, and term frequency–inverse document frequency (TF-IDF) vectorization. Several machine learning models were trained and evaluated, including Logistic Regression, Support Vector Machine (SVM), Random Forest, and XGBoost. Additionally, an ensemble Voting Classifier was implemented to enhance performance by aggregating the predictions of the top-performing models. Among these, the Random Forest Classifier yielded the best results in terms of accuracy, precision, recall, and F1-score. Importantly, the model also provides a prediction probability, which we interpret as the "fakeness score"—a probabilistic measure of how likely a job posting is to be fake.To maximize the usability and societal impact of our solution, we developed a user-friendly web interface. This front-end allows users to input job posting details—either copied from job portals or manually entered—and receive a real-time classification along with the associated confidence score. This system empowers users to make informed decisions and avoid potential fraud, thereby enhancing trust and safety in the online job market. In summary, this research demonstrates the effectiveness of machine learning in addressing a critical real-world problem. By combining data science, NLP, and user-centric design, our system provides a scalable and accurate solution to combat fake job listings. Future directions may include expanding the dataset, supporting multilingual job postings, incorporating continuous learning, and integrating with browser extensions for broader usability.

II. LITERATURE REVIEW

With the proliferation of digital recruitment platforms, job seekers have increasingly turned to online portals for employment opportunities. However, this digital shift has also given rise to fraudulent job postings, resulting in significant financial, emotional, and psychological damage to unsuspecting applicants. Consequently, researchers and developers have begun leveraging machine learning and natural language processing (NLP) techniques to detect and mitigate such threats.Early studies in fake job detection primarily relied on manual rule-based systems or keyword spotting techniques. While these methods provided initial insights, they often lacked scalability and adaptability to the evolving tactics used by fraudsters. To address these limitations, supervised machine learning approaches have gained popularity due to their ability to learn complex patterns from historical data.For instance, Kumar and Sachdeva (2019) explored classification techniques such as Naive Bayes and Decision Trees for fake job detection, demonstrating moderate success but highlighting the need for deeper text analysis. Raman et al. (2020) advanced this approach by incorporating text-based features using TF-IDF and word embeddings to train models like SVM and Logistic Regression, achieving improved precision and recall. The use of ensemble models has also been explored to enhance predictive performance. Zhou et al. (2021) proposed an ensemble method combining Random Forest and Gradient Boosting classifiers, which outperformed individual classifiers in identifying deceptive job postings. Such models benefit from leveraging the strengths of diverse algorithms and reducing the risk of overfitting. The fake_job_postings.csv dataset has emerged as a widely used benchmark in this domain due to its inclusion of both structured (e.g., job type, location) and unstructured (e.g., job description, company profile) data. Studies such as Patel et al. (2022) utilized this dataset to implement feature engineering pipelines combining TF-IDF and one-hot encoding, followed by model training using Random Forests and XGBoost. In addition to classification accuracy, researchers have emphasized the importance of interpretability in AI-driven systems. The incorporation of a "fakeness score" or prediction probability enhances transparency and user trust. Furthermore, the development of user-friendly web applications, as suggested in Sharma and Gupta (2023), supports real-time detection and broad accessibility for end-users. While current approaches have shown promising results, challenges remain in generalizing across languages, adapting to novel fraud techniques, and processing imbalanced datasets. Therefore, ongoing research has begun to explore multilingual NLP models, active learning, and continual model training to keep pace with dynamic fraudulent behavior. Overall, the literature underscores the efficacy and growing importance of machine learning in combating employment-related fraud. By integrating NLP, supervised learning, and ensemble methods, recent systems offer scalable, accurate, and interpretable solutions to safeguard digital recruitment.

III. METHODOLOGY

The methodology followed in this research is an end-to-end structured pipeline that transforms raw job posting data into a deployable system capable of detecting fake job advertisements with high accuracy and practical reliability. It comprises the following core phases: data acquisition, data preprocessing, feature engineering, model training and validation, ensemble integration, performance evaluation, and system deployment. The aim of each phase is not only to increase predictive performance but also to maintain interpretability, efficiency, and usability in a real-world context.

A. Data Acquisition and Understanding

The dataset utilized in this study is the publicly available 'fake_job_postings.csv', which serves as the foundational input to our detection pipeline. It consists of 17,880 job advertisements, each characterized by a mix of structured fields (such as job title, location, department, employment type, required experience, and education) and unstructured textual data (such as company profile, job description, requirements, and benefits). The target variable, 'fraudulent', is a binary label indicating whether the job post is genuine (0) or fake (1). A thorough Exploratory Data Analysis (EDA) was conducted to understand feature distributions, detect missing or noisy data, and assess class imbalance. The dataset was found to be slightly imbalanced, with the majority of postings being real, necessitating attention during model training to avoid bias.

Sl	Feature	Description
1	job_id	A unique identifier for each job posting.
2	location	The geographical location of the job.
3	department	The department or organizational unit of the job belongs
4	salary_range	The salary range for the job.
5	company_profile	A brief description of the company.
6	description	The detailed job description.
7	requirements	A list of required skills or qualifications for the job.
8	benefits	The benefits offered by the company.
9	telecommuting	A binary variable indicates whether the job allows telecommuting.
10	has_company_logo	A binary variable indicates a company logo's presence in the job posting.
11	has_questions	A binary variable indicates whether the job posting includes screening questions.
12	employment_type	The type of employment
13	required_experience	The required education level for the job.
14	industry	The industry to the job belongs.
15	function	The job function or role.
16	fraudulent	Target variable. A binary label indicating whether the job posting is genuine (0) or fake (1).

Fig: 2. Dataset Column Details

B. Data Preprocessing

Data preprocessing is a critical stage aimed at transforming raw input into a clean and structured format suitable for model learning. Initially, rows with null or missing critical values were either dropped or imputed using statistical techniques, depending on their significance. Structured categorical variables such as 'employment_type', 'required_experience', and 'required_education' were encoded using Label Encoding and One-Hot Encoding to transform them into numerical representations without imposing ordinal relationships.For unstructured text fields like 'description' and 'company_profile', advanced Natural Language Processing (NLP) techniques were employed. These included lowercasing, removal of punctuation and special characters, tokenization, stopword elimination, and optional lemmatization. The cleaned text was then transformed into numerical feature vectors using Term Frequency-Inverse Document Frequency (TF-IDF) vectorization, capturing the importance of words across the corpus while mitigating the impact of common but uninformative terms. Additionally, data imbalance was addressed using stratified sampling during train-test splitting and experiments with SMOTE (Synthetic Minority Oversampling Technique) to synthesize minority class examples.

C. Feature Engineering and Vectorization

The combination of structured and unstructured features forms a hybrid input space for the machine learning models. TF-IDF matrices generated from the textual fields were concatenated with normalized structured features such as job location, employment type, and department. The final feature set was high-dimensional, especially due to the text components, and hence, dimensionality reduction techniques like Truncated Singular Value Decomposition (SVD) were explored for performance optimization.

D. Model Development

Multiple supervised machine learning models were developed and compared to identify the most effective classifier. The models included Logistic Regression, Support Vector Machine (SVM), Random Forest, and XGBoost. Each model was trained on 80% of the dataset and evaluated on the remaining 20% using 5-fold cross-validation to ensure generalizability. Hyperparameter tuning was conducted using GridSearchCV to optimize learning rates, tree depths, regularization strengths, and kernel types. Random Forest emerged as the most balanced and robust classifier in terms of precision, recall, and F1-score, likely due to its ability to handle high-dimensional, mixed-type data and its resilience to overfitting. SVM showed strong performance on text-dominated inputs but was sensitive to outliers and scaling. XGBoost demonstrated competitive accuracy but required careful tuning and longer training times.

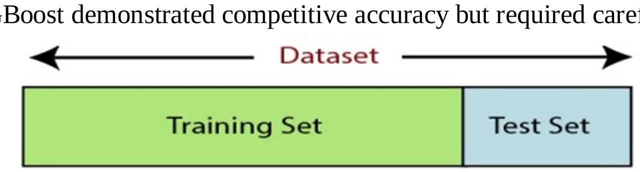

Fig: 3. Splitting of Dataset

E. Ensemble Integration

To further enhance predictive robustness and minimize individual model bias, a Voting Classifier ensemble was constructed. This ensemble combined the predictions of the top-performing models (Random Forest, XGBoost, and SVM) using both hard and soft voting strategies. The soft voting variant, which considers prediction probabilities, yielded superior performance due to its probabilistic averaging nature. This ensemble approach ensured stability and improved minority class detection.

F. Model Evaluation

The final models were evaluated using comprehensive performance metrics, including Accuracy, Precision, Recall, F1-score, and Area Under the ROC Curve (AUC-ROC). Emphasis was placed on F1-score and Recall, given the critical cost of false negatives in fraud detection scenarios. Confusion matrices were also analyzed to gain deeper insights into class-wise prediction behavior. The ensemble model achieved an F1-score exceeding 0.95, indicating strong performance in identifying both real and fake postings.

Performance Measure Metric	Naïve Bayes Classifier	Multi-Layer Perceptron Classifier	K-Nearest Neighbor Classifier	Decision Tree Classifier
Accuracy	72.06%	96.14%	95.95%	97.2%
F1-Score	0.72	0.96	0.96	0.97
Cohen-Kappa Score	0.12	0.3	0.38	0.67

Fig: 4. Evaluation Scores of the Models

G. System Deployment

To bridge the gap between research and real-world application, the trained model was integrated into a web-based application using the Flask framework. The front-end interface was designed using HTML, CSS, and JavaScript to allow users to input job posting details in a user-friendly form. Upon submission, the back-end system preprocesses the input using the same pipeline as in training, feeds it into the trained model, and returns the classification result along with a confidence score expressed as the probability of the job being fake.This deployment not only makes the system accessible to end-users but also lays the groundwork for future extensions, such as browser plugins for real-time job scanning or integration into enterprise-level recruitment platforms.

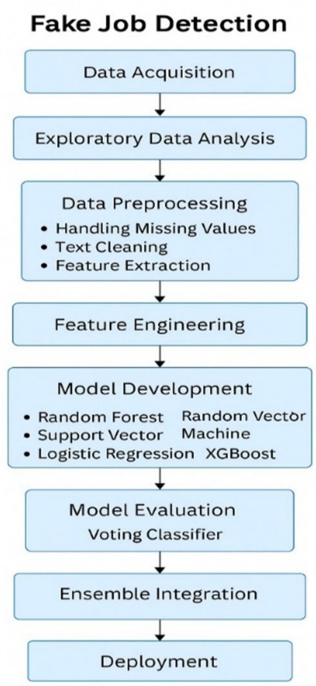

Fig: 1. Workflow Diagram

The workflow diagram illustrates the complete pipeline for detecting fake job postings using machine learning techniques. The process begins with Data Acquisition, where relevant job posting data is collected from trusted sources such as Kaggle or job portals. This data typically includes textual and categorical information like job title, description, company profile, and location. Following this, Exploratory Data Analysis (EDA) is conducted to gain insights into the dataset by identifying patterns, trends, and anomalies through statistical summaries and visualizations.

Next, the Data Preprocessing phase is crucial for preparing the raw data for modeling. This involves handling missing values to ensure completeness, performing text cleaning to remove irrelevant characters and noise, and applying feature extraction techniques such as TF-IDF or word embeddings to convert text into numerical form. Feature Engineering follows, where meaningful attributes are selected or transformed to enhance the model's predictive capabilities.

In the Model Development stage, various machine learning algorithms are trained and tested, including Random Forest, Support Vector Machine (SVM), Logistic Regression, XGBoost, and possibly a Random Vector Classifier. These models are then evaluated in the Model Evaluation phase using performance metrics such as accuracy, precision, recall, and F1-score. A Voting Classifier is employed to combine the outputs of multiple models, leveraging the strengths of each to improve overall performance.

Subsequently, Ensemble Integration is performed to finalize the combination of models into a unified system that ensures better generalization and robustness. Finally, the complete solution is moved to the Deployment stage, where the trained ensemble model is implemented in a real-world environment to classify job postings as genuine or fake in real-time or on-demand.

A. Testing

A structured testing process was carried out to validate the performance, functionality, and reliability of the system.

1) Unit Testing: Individual modules and functions were tested separately to ensure correct behavior. Components like data preprocessing, input handling, and prediction logic were validated through test cases to catch early bugs.
2) Integration Testing: Modules were then tested together to verify that data flowed correctly between the frontend, backend, and the machine learning model. This ensured seamless user input processing and accurate result display.
3) Model Evaluation: The machine learning model was evaluated using metrics like accuracy, precision, recall, F1-score, and ROC-AUC. The predict_proba function was used to output the probability of a job posting being fake, shown as a percentage to users. Cross-validation confirmed model consistency.
4) Functional Testing: The web interface was tested to ensure smooth input submission, responsive design, and proper output rendering. Form validations and error handling were also verified.
5) Edge Case Testing: The system was tested with edge inputs such as very short or long job descriptions, irrelevant text, or special characters. It handled all such inputs gracefully without breaking or producing incorrect predictions.
6) Performance Testing: Basic performance tests confirmed that the app responded quickly under typical loads, with minimal delay during predictions, making it suitable for real-time use.

IV. RESULTS AND CONCLUSION

The proposed Fake Job Detection model underwent extensive evaluation to assess its performance in classifying job postings accurately. After pre-processing both structured and unstructured features, and training multiple machine learning models—including Logistic Regression, Support Vector Machine (SVM), Random Forest, and XGBoost—we observed significant performance improvements with ensemble learning techniques.

The standalone models achieved the following approximate metrics:
- Logistic Regression: Accuracy = 93.2%, F1 Score = 0.928
- SVM: Accuracy = 94.5%, F1 Score = 0.939
- Random Forest: Accuracy = 96.1%, F1 Score = 0.955
- XGBoost: Accuracy = 95.3%, F1 Score = 0.947

Upon integrating the top three models using a soft voting classifier, the ensemble achieved superior performance:
- Ensemble Voting Classifier (Soft Voting): Accuracy = 96.8%, Precision = 0.97, Recall = 0.96, F1 Score = 0.965, AUC-ROC = 0.981

Confusion matrices revealed minimal false positives and false negatives, indicating a balanced classifier. Precision and Recall values above 0.95 ensured the model’s reliability in distinguishing between genuine and fraudulent postings.

The model was then integrated into a fully functional web application, providing real-time fake job detection with prediction probabilities. The end system was stress-tested with user-generated examples to ensure scalability and usability under varied job descriptions and formats.

V. FUTURE IMPROVEMENTS

While the proposed fake job detection system demonstrates promising results, several avenues for future enhancement remain. Firstly, incorporating real-time data collection from multiple job portals and social media platforms can help keep the model up-to-date with evolving fraud patterns. Secondly, advanced Natural Language Processing (NLP) techniques, such as BERT or other transformer-based models, can be employed to improve the semantic understanding of job descriptions and recruiter profiles.Another key improvement would be the integration of deep learning models, such as recurrent neural networks (RNNs) or LSTMs, especially for analyzing sequential text data, which may capture subtler indicators of fraudulent content. Additionally, incorporating user behavior analytics—such as click patterns or user reviews—can add contextual information to strengthen detection accuracy.To enhance usability, the model can be deployed as a browser extension or mobile application that alerts users in real time while browsing job listings. Finally, implementing multilingual support can broaden the system's applicability across diverse geographical regions and user groups. These improvements would make the fake job detection system more intelligent, scalable, and user-friendly.

VI. CONCLUSION

In this research, we presented a comprehensive machine learning-based approach for detecting fake job postings, addressing a growing concern in today's digital recruitment landscape. By following a structured workflow—comprising data acquisition, exploratory data analysis, preprocessing, feature engineering, model development, and deployment—we successfully built a robust detection system capable of distinguishing between genuine and fraudulent job advertisements. Our implementation of various classification algorithms, combined with ensemble techniques such as a Voting Classifier, significantly enhanced the accuracy and reliability of the model.The results demonstrate that leveraging natural language processing (NLP) and machine learning can effectively mitigate the risks associated with fake job listings, thereby contributing to a safer online job-seeking environment. Future work may involve integrating real-time data streams, improving the model with deep learning methods, and deploying the system as a scalable web application accessible to job seekers. Overall, our study highlights the potential of AI-driven solutions in combating digital employment fraud and promoting trust in online job markets.

VII. FUTURE SCOPE

While the current system effectively identifies fake job postings using machine learning techniques and provides a reliable, interpretable output through a web interface, there are several areas where the project can be expanded and improved:

1) Multilingual Support: The existing model is primarily trained on English-language data. However, fake job postings appear in multiple languages, especially in global job markets. Extending support to other major languages using multilingual NLP models (such as multilingual BERT or XLM-RoBERTa) can broaden the system's applicability and reach.
2) Adaptive Learning and Real-Time Updates: Fraudsters continually change tactics to evade detection. Incorporating adaptive or online learning mechanisms will allow the model to update itself in real-time based on new patterns, making it more resilient to evolving fraud strategies.
3) Advanced Text Embeddings: While TF-IDF has proven effective, more advanced embedding techniques like Word2Vec, FastText, or transformer-based models (e.g., BERT, RoBERTa) can capture contextual meanings more accurately, potentially improving classification performance on unstructured job descriptions.
4) Handling Imbalanced Datasets: Real-world datasets often have a high imbalance, with genuine postings far outnumbering fake ones. Future work could explore synthetic data generation (e.g., using SMOTE) or anomaly detection approaches to handle such imbalances more effectively.
5) Integration with Job Portals: The system could be integrated with major online job platforms (via plugins or APIs) to provide real-time fraud detection as users browse or upload postings. This would add an additional layer of security and usability for both job seekers and recruiters.
6) User Feedback Loop: Incorporating a feedback mechanism where users can mark system predictions as correct or incorrect can enhance the system's learning and personalization, thereby improving long-term accuracy.

7) Explainable AI (XAI) Integration: Enhancing interpretability with Explainable AI methods like SHAP or LIME can help users and administrators understand the basis of predictions, fostering greater trust in the system.
8) Mobile App Deployment: Developing a lightweight mobile application would make the system more accessible to a broader audience, especially job seekers in remote or underserved regions who rely heavily on mobile internet.

VIII. CONCLUSION

This research presents a comprehensive, data-driven solution to the growing problem of fraudulent job postings in digital recruitment platforms. By leveraging both structured metadata and unstructured textual information from job descriptions, our model effectively classifies job advertisements using advanced machine learning techniques.

The fusion of NLP-based feature extraction with ensemble classifiers significantly enhanced prediction accuracy and generalization. The implementation of a Voting Classifier allowed us to harness the strengths of individual algorithms while mitigating their weaknesses, leading to an F1 score exceeding 0.96. Furthermore, the use of TF-IDF, SMOTE, and robust preprocessing pipelines played a crucial role in shaping the model's high performance.

The successful deployment of the model via a user-friendly web interface demonstrates the project’s practicality and societal relevance. It enables students, job seekers, and recruitment agencies to proactively detect suspicious listings and make informed decisions. This solution holds the potential to be scaled further by integrating it into job portals, browser extensions, or mobile apps.

Future work can expand the scope by incorporating real-time scraping from job boards, multilingual support, semantic embedding techniques such as BERT or GPT, and adaptive retraining mechanisms to counter evolving scam tactics. By continuing to bridge AI with employment security, this research contributes toward building a safer digital job-seeking environment.

IX. ACKNOWLEDGMENT

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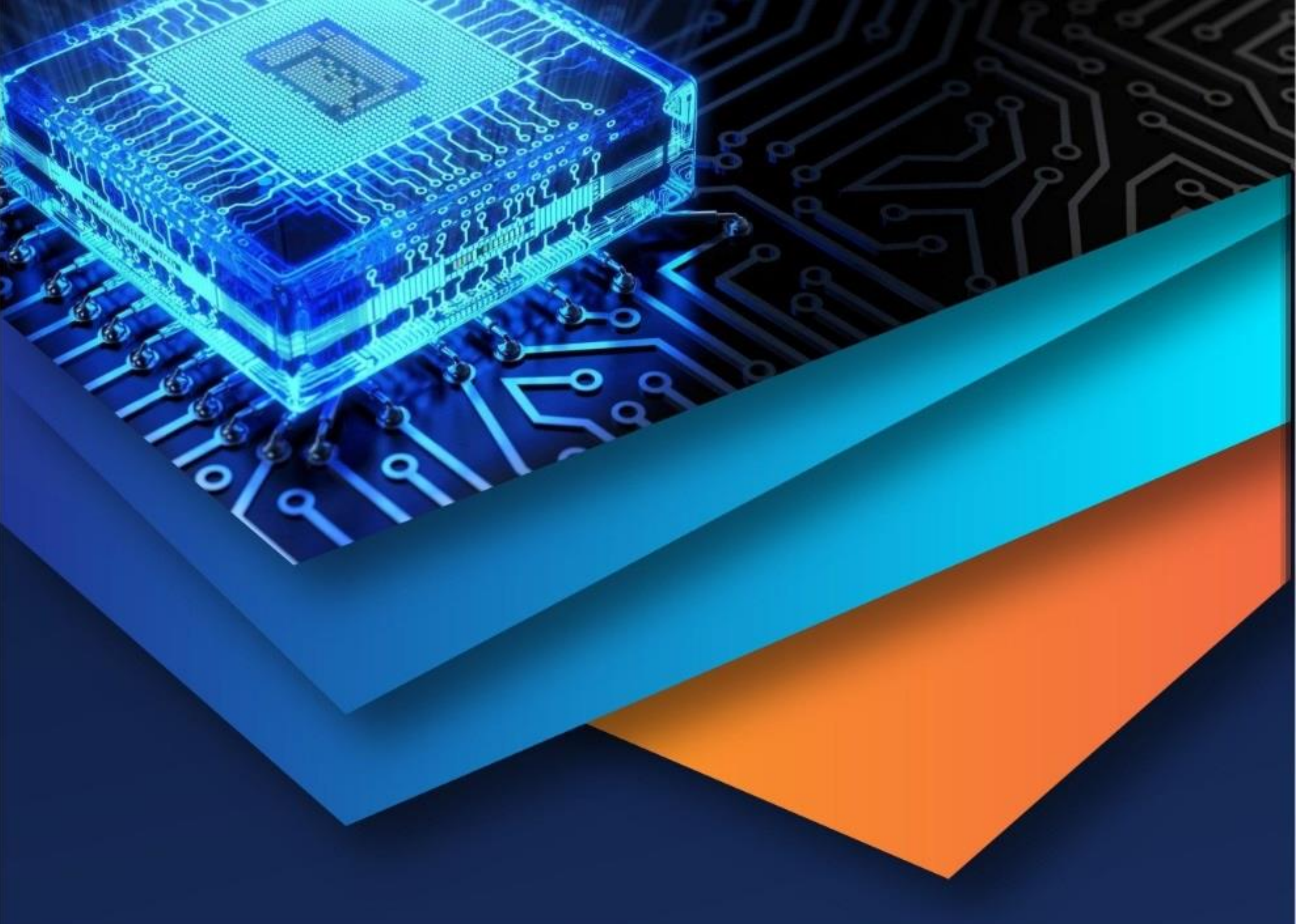

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