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An Intelligent Cyber Threat Detection Framework Using a Hybrid Convolutional Neural Network-Long Short-Term Memory (CNN-LSTM) Machine Learning Mode

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Abstract: ***The attack surface for contemporary cyber threats has greatly increased due to the growing reliance on networked digital systems and internet-driven services. Conventional security solutions that rely on static signatures and predetermined rules are no longer adequate as cyberattacks become more sophisticated and adaptable.***
Due to these conventional methods' inability to detect new and zero-day threats, network infrastructures are more vulnerable and detection is delayed. This paper offers an intelligent cyber threat detection framework based on a hybrid deep learning architecture that combines Long Short-Term Memory (LSTM) networks with Convolutional Neural Networks (CNN) in order to get around these restrictions.
The suggested system does away with the requirement for human feature engineering by using the CNN module to automatically learn and extract significant spatial patterns from network traffic features. The detection of intricate and dynamic attack patterns is therefore made possible by using the LSTM module to represent the temporal linkages and sequential behaviors found in network traffic flows. Widely used intrusion detection datasets are used to verify the efficacy of the suggested model. Standard criteria, such as accuracy, precision, recall, F1-score, and false positive rate, are used to evaluate performance. According to experimental results, the hybrid CNN–LSTM architecture regularly outperforms both individual deep learning models and traditional machine learning techniques in terms of detection performance. The proposed approach demonstrates strong generalization capability and is well suited for real-time deployment in dynamic cybersecurity environments.
Keywords: Cybersecurity, Intrusion Detection System, CNN–LSTM, Deep Learning, Threat Detection, Machine Learning.

I. INTRODUCTION

The complexity and size of contemporary network infrastructures have greatly risen due to the quick development of digital communication technologies, cloud-based services, and Internet of Things (IoT) ecosystems. These developments present significant cybersecurity risks even as they facilitate continuous connectivity and data flow. Diverse and sophisticated cyberattacks, such as ransomware campaigns, denial-ofservice (DoS) attacks, malware infections, and advanced persistent threats (APTs), are increasingly targeting modern networks. Static rules and preconfigured signatures are the main components of traditional security measures like firewalls and rule-based intrusion detection systems (IDS). Because of this, current methods are unable to identify assaults that have never been seen before or adjust to constantly changing threat patterns.

Machine learning (ML) approaches have drawn interest as clever solutions for cyber threat identification in order to overcome these constraints. ML-based systems are able to automatically identify deviations linked to malicious activity by learning behavioral patterns from network traffic data. Despite their benefits, traditional machine learning algorithms frequently need a lot of human feature engineering and are not very good at simulating the intricate temporal correlations present in network traffic flows. Their ability to identify multi-stage and covert assault activities is diminished by this limitation.

Deep learning models have shown a great deal of promise in resolving these issues. While Long Short-Term Memory (LSTM) networks are excellent at learning long-term temporal correlations in sequential data, Convolutional Neural Networks (CNNs) are very good at extracting spatial characteristics from high-dimensional data. Nevertheless, each model only tackles a portion of the issue when applied separately.

In this regard, a hybrid CNN–LSTM architecture-based intelligent cyber threat detection framework is proposed in this research. Instead of depending on manually created characteristics, the CNN component is used to automatically extract discriminative spatial features from network traffic data. The LSTM component then processes these extracted representations to identify sequential attack patterns and temporal correlations. The suggested architecture is appropriate for deployment in dynamic and real-time cybersecurity situations because it combines the complementary strengths of CNN and LSTM models to enable accurate identification of both known and new cyber threats.

II. RELATED WORK

The use of machine learning and deep learning algorithms for efficient cyber threat identification has become a major focus of recent developments in cybersecurity research. Because of their ease of use and interpretability, traditional machine learning techniques like Support Vector Machines (SVM), Random Forest (RF), and K-Nearest Neighbors (KNN) have been widely used in intrusion detection systems. These methods show respectable detection accuracy for well-known assault patterns, although they mostly rely on hand-crafted qualities and manual feature selection. As a result, their capacity to adjust to new and changing attack scenarios is still restricted.

Deep learning-based approaches have drawn a lot of interest as a solution to these problems. In order to improve classification performance, Convolutional Neural Network (CNN) models are frequently used to automatically extract discriminative spatial features from network traffic data. In a similar vein, Long Short-Term Memory (LSTM) networks are useful for simulating the sequential actions and temporal linkages connected to cyberattacks. While solo LSTM models frequently struggle to comprehend high-dimensional feature spaces, independent CNN models, despite their particular capabilities, are unable to grasp long-term temporal dependencies.

Hybrid CNN–LSTM architectures, which combine temporal sequence modeling and spatial feature learning, have been developed to address these issues. Studies already conducted show that hybrid models improve detection accuracy and lower false alarm rates. However, a lot of these methods have limited scalability and significant processing complexity, which limits their use in real-time settings. By putting out an effective and scalable CNN–LSTM system designed for clever and useful cyber threat identification, this work expands on earlier studies.

III. PROPOSED METHODOLOGY AND SYSTEM ARCHITECTURE

A. Framework Overview

By combining deep learning methods for both spatial and temporal analysis of network traffic data, the suggested intelligent cyber threat detection framework is intended to precisely detect hostile activity in network environments. To guarantee effective feature learning, dependable threat classification, and rapid data processing, the system employs a structured, multi-stage pipeline.

Table 1. Proposed CNN–LSTM Cyber Threat Detection Framework Overview

Stage No.	Framework Stage	Description
1	Data Collection	Network traffic data is collected from standard intrusion detection datasets or real-time monitoring sources, containing both normal and attack instances.
2	Data Preprocessing and Normalization	Raw data is cleaned by handling missing values, encoding categorical features, and normalizing numerical attributes to ensure consistent input scaling.
3	Feature Extraction using CNN	Convolutional Neural Network (CNN) layers automatically extract spatial and local feature patterns from the preprocessed network traffic data.
4	Temporal Learning using LSTM	Long Short-Term Memory (LSTM) networks analyze sequential dependencies and temporal behaviors present in network traffic flows.
5	Threat Classification	Fully connected layers classify traffic instances as normal or malicious based on learned spatial–temporal representations.
6	Performance Evaluation	The framework performance is evaluated using standard metrics such as accuracy, precision, recall, F1-score, and false positive rate (FPR).

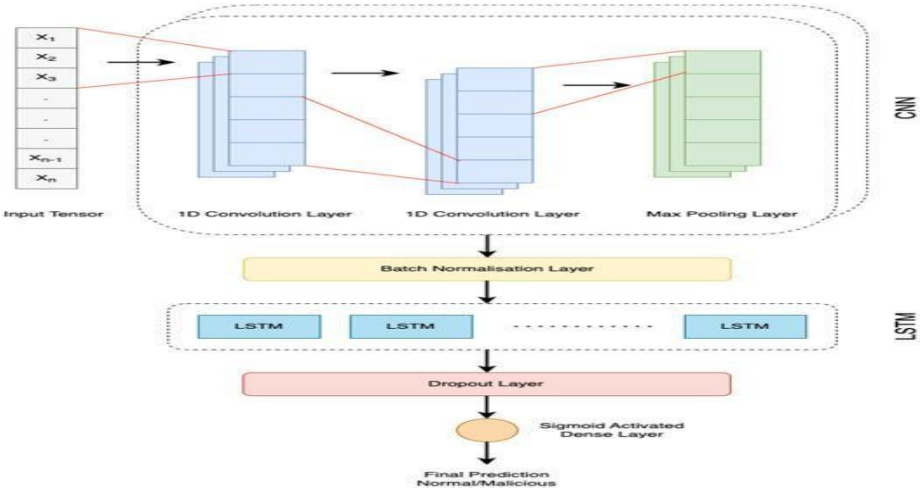

Fig. 1 Proposed CNN–LSTM Cyber Threat Detection Framework

Data collection is the first step in the process. Network traffic data is gathered via datasets or real-time monitoring devices. In order to eliminate noise, deal with missing values, and scale features for effective learning, the gathered data is then preprocessed and standardized. After that, a CNN module automatically extracts local patterns and spatial information from the network traffic. The LSTM module receives these extracted features and uses them to learn sequential attack behaviors and temporal dependencies. The system performs threat classification by classifying traffic as either harmful or normal based on the learnt spatial-temporal properties. Lastly, performance evaluation utilizing metrics including accuracy, precision, recall, and F1-score validates the model's efficacy.

B. Implementation Architecture

The suggested cyber threat detection framework's implementation architecture is made to effectively handle network traffic data and precisely categorize harmful activity. Network traffic records, which are made up of many attributes that reflect network communication behavior, are fed into the architecture. The Convolutional Neural Network (CNN) layer, the first part of the design, is in charge of extracting significant spatial elements from the incoming traffic data. The CNN automatically discovers discriminative patterns and local correlations among network features by using convolution and pooling procedures.

The Long Short-Term Memory (LSTM) layer receives the extracted feature representations and uses them to learn sequential behaviors and temporal dependencies found in network traffic flows. By capturing long-term contextual information, the LSTM layer makes it possible to identify intricate and dynamic attack patterns.

The architecture uses a Fully Connected (Dense) layer to carry out final classification after temporal learning. The learnt spatial-temporal properties are mapped to output classes by this layer.

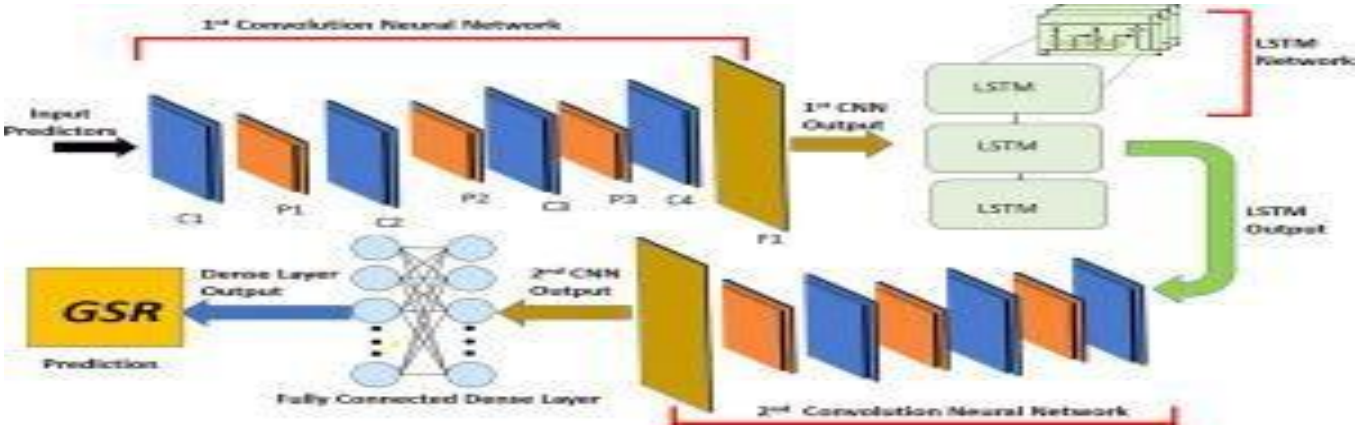

Fig. 2 Implementation Architecture of CNN LSTM

The system's final output provides an efficient decisionmaking mechanism for intelligent cyber threat identification by classifying network traffic as either Normal or Attack.

IV. HYBRID CNN–LSTM ALGORITHM

Input: Network traffic dataset
Output: Classified traffic (Normal / Attack)

1) Open the dataset of network traffic that includes both benign and malevolent incidents.
2) Preprocess the dataset by normalizing numerical features, addressing missing values, encoding category variables, and eliminating noise.
3) Convert the pre-processed data into a temporal learning appropriate sequential format.
4) To automatically extract spatial information from the input data, use Convolutional Neural Network (CNN) layers.
5) To understand temporal dependencies and sequential attack patterns, send the retrieved feature representations to Long Short-Term Memory (LSTM) layers.
6) Use labelled training data to train the hybrid CNN– LSTM model.
7) To evaluate the generalization performance of the trained model, use test samples that have not yet been seen.

Based on the model's forecast, categorize every occurrence of network traffic as either malicious or normal.

V. IMPLEMENTATION AND CODING

A. *Tools and Technologies*

The proposed hybrid CNN–LSTM cyber threat detection framework is implemented using widely adopted opensource tools and libraries that support efficient data processing and deep learning model development.

1) Python: Python is used as the primary programming language due to its simplicity, flexibility, and extensive ecosystem of libraries for data analysis and machine learning.
2) Tensor Flow / Keras: TensorFlow, along with the Keras high-level API, is employed for designing, training, and evaluating the hybrid CNN–LSTM deep learning model. These frameworks provide efficient support for neural network construction and GPU acceleration.
3) NumPy and Pandas: NumPy is utilized for numerical computations and matrix operations, while Pandas is used for data loading, preprocessing, and manipulation of network traffic datasets.
4) Scikit-learn: Scikit-learn is used for data preprocessing tasks such as normalization, encoding, dataset splitting, and performance evaluation using standard metrics.

B. *Sample CNN–LSTM Implementation (Pseudocode)*

Algorithm: CNN–LSTM Based Cyber Threat Detection
Input: Network traffic dataset D with features X and labels Y
Output: Classified network traffic (Normal / Malicious)
1. Load dataset D 2. Preprocess data:
a. Handle missing values
b. Encode categorical features
c. Normalize numerical features
3. Split dataset into training set (X_train, Y_train) and test set (X_test, Y_test)
4. Reshape input data to sequential format suitable for CNN-LSTM
5. Initialize CNN–LSTM model:
    a. Add Conv1D layers to extract spatial features
    b. Add MaxPooling1D layers to reduce dimensionality
    c. Add LSTM layers to learn temporal dependencies
    d. Add Dropout layers to prevent overfitting
    e. Add Fully Connected (Dense) layer with sigmoid/SoftMax activation for classification Compile model with appropriate optimizer (e.g., Adam) and loss function (e.g., binary_crossentropy)
6. Train model on (X_train, Y_train) for N epochs with batch size B
7. Evaluate model performance on (X_test, Y_test)
8. For each test sample:
    a. Predict class label using trained model
    b. Classify as Normal or Malicious

9. Compute performance metrics:
    a. Accuracy
    b. Precision
    c. Recall
    d. F1-score

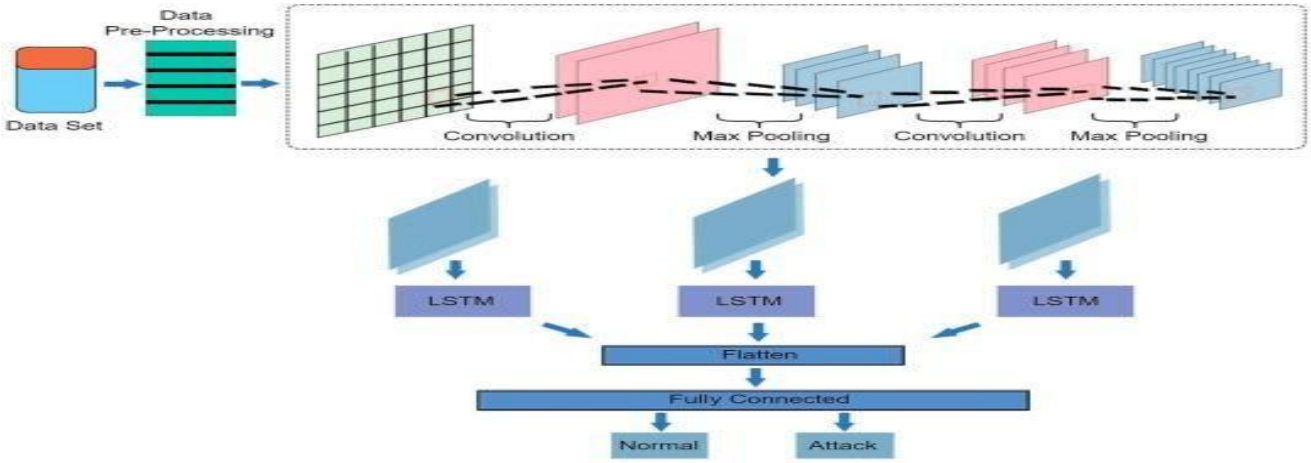

Fig. 3 CNN–LSTM cyber threat detection flowchart

VI. APPLICATIONS

The proposed hybrid CNN–LSTM cyber threat detection framework has wide applicability in modern networked and IoT environments. Its ability to automatically learn spatial and temporal patterns from network traffic makes it suitable for various cybersecurity scenarios, including:

Network Intrusion Detection Systems (NIDS): Detects malicious activities and abnormal traffic patterns in enterprise and organizational networks.

IoT Security Monitoring: Secures IoT devices and communication networks by identifying anomalous or suspicious behavior in resource-constrained environments.

1) Cloud Infrastructure Security: Enhances protection of cloud-based systems by monitoring traffic and detecting potential attacks on virtualized resources.

2) Enterprise Network Protection: Safeguards corporate networks from cyberattacks, including malware, ransomware, and advanced persistent threats (APTs).

3) Real-Time Traffic Analysis: Enables continuous monitoring and immediate classification of network packets to support rapid threat mitigation.

4) Smart Grid and Critical Infrastructure Security: Protects critical systems such as smart grids, industrial control networks, and energy management systems against cyber intrusions.

Table 2. Applications of the CNN–LSTM Threat Detection Framework

S. No.	Application	Description
1	Network Intrusion Detection Systems (NIDS)	Detects abnormal and malicious traffic patterns in enterprise and organizational networks.
2	IoT Security Monitoring	Secures IoT devices and communication networks by identifying anomalies in resource-constrained environments.
3	Cloud Infrastructure Security	Monitors and protects cloud-based systems, including virtualized resources, from potential attacks.
4	Enterprise Network Protection	Safeguards corporate networks against malware, ransomware, and advanced persistent threats (APTs).
5	Real-Time Traffic Analysis	Enables continuous monitoring and immediate classification of network packets for rapid threat mitigation.
6	Smart Grid Critical Infrastructure Security	Protects critical systems, such as smart grids and industrial control networks, from cyber intrusions.

VII. PERFORMANCE EVALUATION

The effectiveness of the proposed hybrid CNN–LSTM cyber threat detection framework is evaluated using commonly adopted performance metrics in cybersecurity and machine learning. These metrics provide insights into both the accuracy of the model and its reliability in detecting malicious activities.

A. *Performance Metrics:*

1) Accuracy: Measures the overall proportion of correctly classified instances (both normal and malicious).
2) Precision: Indicates the proportion of correctly predicted malicious traffic among all instances predicted as malicious.
3) Recall (Sensitivity): Represents the proportion of actual malicious instances correctly identified by the model.
4) F1-Score: Harmonic mean of precision and recall, providing a single metric for model effectiveness.
5) False Positive Rate (FPR): Proportion of normal traffic incorrectly classified as malicious, reflecting the likelihood of false alarms.

Table 3. Performance Comparison of Different Models

Model	Accuracy (%)	Precisio n (%)	Recall (%)	F1Score (%)	FPR (%)
SVM	89.2	87.5	85.6	86.5	10.4
Random Forest (RF)	91.8	90.2	88.7	89.4	8.9
Hybrid CNN– LSTM	96.5	95.8	94.9	95.3	4.2

The results demonstrate that the hybrid CNN–LSTM model outperforms traditional machine learning methods such as SVM and Random Forest. It achieves higher accuracy, better balance between precision and recall, and significantly lower false positive rates, indicating its robustness and reliability for real-time cyber threat detection in dynamic network environments.

VIII. FUTURE SCOPE

The proposed hybrid CNN–LSTM framework provides an effective solution for intelligent cyber threat detection, yet there are several avenues for further research and improvement.

1) Federated Learning Integration: Future work can explore federated learning to enable privacy-preserving threat detection. This approach allows multiple distributed devices or networks to collaboratively train a global model without sharing raw data, protecting sensitive information.
2) Lightweight Edge Deployment: Developing lightweight versions of the CNN–LSTM model will allow deployment on resource-constrained edge devices, such as IoT sensors and mobile devices, enabling real-time threat detection closer to the data source.
3) Explainable AI (XAI): Incorporating explainability into the model will help interpret the reasoning behind detection results. XAI techniques can provide insights into which features or sequences triggered an alert, improving trust and adoption in critical applications.
4) Real-Time Streaming Data Implementation: Extending the framework to process continuous streaming network data can enhance real-time detection capabilities, allowing immediate response to emerging threats.
5) Blockchain-Enabled Secure Data Sharing: Combining blockchain technology with the framework can ensure secure and tamper-proof data sharing between multiple stakeholders, enhancing the reliability and integrity of threat intelligence across distributed networks.

These future enhancements aim to make the hybrid CNN– LSTM framework more scalable, interpretable, and deployable in real-world networked and IoT environments, addressing the growing challenges of cybersecurity in dynamic and distributed systems.

IX. CONCLUSION

This paper proposed an intelligent cyber threat detection framework leveraging a hybrid CNN–LSTM machine learning model. By integrating the spatial feature extraction capabilities of CNN with the temporal sequence modeling strength of LSTM, the framework effectively identifies both known and previously unseen cyber threats. Experimental evaluation on standard intrusion detection datasets demonstrates that the hybrid model outperforms traditional machine learning techniques such as SVM and Random Forest, achieving higher accuracy, improved precision and recall, and reduced false positive rates.

The proposed approach is not only robust in detecting complex attack patterns but also exhibits strong generalization, making it suitable for deployment in dynamic, large-scale, and real-time network environments. Moreover, its adaptability and scalability indicate significant potential for securing IoT systems, cloud infrastructures, enterprise networks, and critical infrastructures. Future enhancements, including lightweight edge deployment, federated learning, and explainable AI, can further strengthen the practical applicability of the framework, making it a promising solution for modern cybersecurity challenges.

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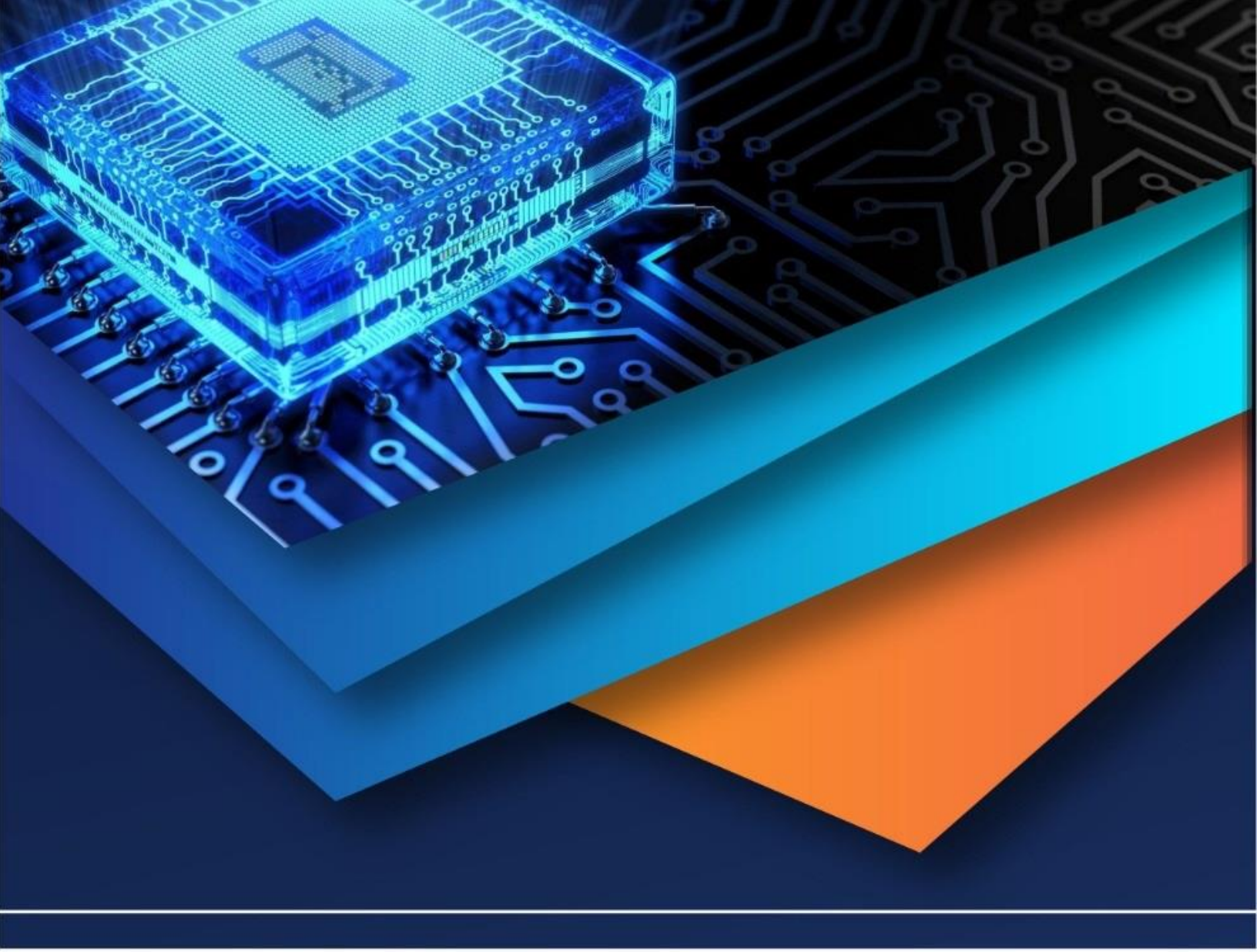

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