iJRASET
International Journal For Research in Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 13 **Issue:** IX **Month of publication:** September 2025

DOI: https://doi.org/10.22214/ijraset.2025.74079

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International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue IX Sep 2025- Available at www.ijraset.com

Detecting Deepfake Faces with CNN and LSTM

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Abstract: ***In recent years, the advent of deepfake technology has posed significant challenges to the veracity of digital content. Originally emerging as an offshoot of advancements in generative modelling, deep fakes have evolved into sophisticated tools capable of creating hyper-realistic yet entirely synthetic facial content in videos and images. These manipulations pose serious threats across various sectors including journalism, law enforcement, politics, and social media by enabling the spread of misinformation, identity fraud, and reputational damage.***
To address these growing concerns, this investigation proposes an integrated deepfake detection system utilizing Convolutional Neural Networks. Convolutional Neural Networks (CNNs) are employed for the extraction of spatial features across individual frames, enabling the identification of discrepancies such as artificial textures or visual anomalies. LSTMs complement this by modeling temporal dependencies across frame sequences to detect anomalies in facial movements and expressions. The combined framework enables the system to assess both static and dynamic patterns typical of deepfake manipulations.
The model has undergone training and testing on a comprehensive dataset containing authentic and manipulated media. demonstrating high detection accuracy. Experimental evaluation reveals that the CNN-LSTM hybrid outperforms traditional static analysis models in identifying complex temporal inconsistencies, making it highly effective for video-based deepfake detection. Visualization modules and a user-friendly interface further support real-time use cases, enhancing interpretability and deployment potential in real-world scenarios.
Keywords: Deepfake detection, Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM),temporal examination, facial manipulation, misinformation, video forensics, real-time detection, hybrid deep learning, media authenticity.

I. INTRODUCTION

In recent times, the emergence of deep learning has revolutionized various aspects of artificial intelligence, enabling machines to perform tasks that were once thought to require human cognition. A prominent advancement is the proliferation of deepfake technology, which has elicited substantial apprehensions owing to its potential for misuse.

Deepfakes are hyper-realistic synthetic media particularly videos generated using techniques such as Generative Adversarial Networks (GANs) or autoencoders, where a person's face or voice can be digitally replaced or manipulated to create fabricated content that is nearly indistinguishable from real recordings. The proliferation of deepfakes within entertainment, education, and virtual reality demonstrates their positive potential; however, their unregulated dissemination online presents a significant risk to digital confidence, political equilibrium, societal cohesion, and personal privacy.

As computational power becomes more affordable and open-source repositories make sophisticated deepfake algorithms easily accessible, The development and dissemination of altered content are no longer confined to specialists. Nowadays, individuals with minimal technical expertise can produce compelling deepfakes., leading to their widespread use in fake news, financial fraud, cyberbullying, blackmail, and disinformation campaigns. Deepfake videos have been employed to simulate world leaders, celebrities, and professionals, creating fabricated events and statements that can go viral before any verification is possible. This emphasizes the urgent need for reliable and flexible deepfake detection systems that can operate efficiently in real-world situations.

Moreover, conventional detection techniques typically analyze frames in isolation, failing to capture temporal inconsistencies across video sequences. For instance, a deepfake might produce realistic single frames, but it could introduce subtle errors over time such as abnormal blinking patterns, inconsistent mouth movement, or facial feature shifts that would be undetectable in static analysis. These limitations highlight the necessity of dynamic, Analytic systems with the ability to analyze the spatial and temporal facets of video material. To address these limitations, this study proposes a hybrid deepfake detection framework that combines Convolutional Neural Networks (CNNs) with Long Short-Term Memory (LSTM) networks. The CNN module excels in examining the spatial arrangement of every video frame identifying pixel-level anomalies, unnatural textures, and local distortions. In parallel, The LSTM network created for processing sequential data models the time-based connections between adjacent frames learning motion continuity, expression dynamics, and behavioral transitions over time.

This dual-layered architecture enables the system to evaluate both whatappears in the video and its development creating a more holistic and robust detection pipeline capable of uncovering sophisticated forgeries.

The system is trained and assessed on widely used six benchmark datasets, which include FaceForensics++ and DFDC (Deepfake Detection Challenge) datasets which contain real and manipulated video clips labeled for supervised learning. Preprocessing involves detecting faces, extracting frames, resizing, and normalizing imagesand sequence construction. During training, the model learns both frame-level features and temporal trajectories, aiming to differentiate real content from counterfeits. Various performance metrics, including accuracy, precision, recall, F1-score, and Area Under the Receiver Operating Characteristic Curve (AUC-ROC), are employed to assess the model's performance across different testing scenarios.

Visual outputs such as heatmaps and prediction confidence scores are also generated to enhance explainability and clinical trust, especially for non-technical end users.

The significance of this research extends beyond technical excellence. In a digital environment where misinformation spreads rapidly and verification often lags behind, this work provides a proactive solution to safeguard public discourse and digital credibility. Journalists, fact-checkers, social media moderators, Law enforcement agencies can derive advantages from tools that rapidly evaluate whether video content has been altered.

Furthermore, the integration of this system into real-time applications such as browser plugins, content moderation APIs.

II. LITERATURE SURVEY

The rapid advancement of deepfake technology has spurred a growing emphasis on using artificial intelligence to identify altered media. MesoNet, a key contribution in this domain by Afchar et al. [1], employs a shallow Convolutional Neural Network (CNN) design to capture mesoscopic features and compression artifacts characteristic of deepfakes. While MesoNet is lightweight and well-suited for real-time use, its limited depth hinders its ability to detect subtle forgeries effectively. In complement, Rössler et al. [2] introduced the Face Forensics++ dataset and conducted a comparative analysis of various CNN models for deepfake detection. Their results emphasize the significance of extensive, annotated datasets in training accurate classifiers and illustrate the performance disparity between identifying manipulated and authentic videos across different compression levels.

Researchers recognized the drawbacks of static frame-based methods and started integrating temporal modelling techniques. Sabir et al. [3] combined Convolutional Neural Networks (CNNs) with Recurrent Neural Networks (RNNs) to track facial movements using video frames.allowing the system to detect unusual temporal distortions. Similarly, Guera andDelp [4] proposed a hybrid architecture that employed Convolutional Neural Networks (CNNs) to extract features on a frame-by-frame basis, combined with Long Short-Term Memory (LSTM) networks to capture temporal patterns at the sequence level.. Their method showcased improved performance in detecting discrepancies over time, enhancing the identification accuracy in high-quality manipulated videos.

An innovative approach was introduced by Zhou et al. [5] through the concept of Face X-ray, which focuses on identifying blending boundaries between real and fake facial regions using supervised CNNs. This approach improved not just the detection accuracy, but also offered interpretability via visual hints. On a different note, Li and others [6].

explored physiological features like eye blinking patternsoften missing in deepfakesand built a temporal CNN to flag unnatural blinking behavior, thereby revealing manipulation through behavioral inconsistencies.

To tackle issues related to model generalization, Dang et al. [7] implemented a multi-task learning framework that simultaneously classifies and reconstructs features, thus enabling robust detection across various deepfake types and datasets. Furthermore, Dolhansky et al. [8] contributed the Deepfake Detection Challenge (DFDC) dataset, encouraging the development of scalable and generalizable solutions capable of functioning under real-world constraints such as low resolution, occlusion, and lighting variability.

Explainability has also emerged as a vital component in forensic AI tools. Ribeiro et al. [9] presented the Local Interpretable Model-agnostic Explanations (LIME) method, which identifies the areas within an image that impact a model’s prediction.. When applied to deepfake detection, such frameworks help bridge the gap between model decision and human trust. Similar tools like SHAP further strengthen model transparency, allowing integration into forensic workflows and aiding legal and journalistic review.

Finally, Pearson’s early contribution to feature reduction and Han et al.'s foundational work in machine learning [10] continue to underpin modern techniques such as Principal Component Analysis (PCA) and correlation analysis, Frequently used for pre-processing and reducing dimensionality. These approaches improve the effectiveness and comprehensibility of deep learning models.

III. PROPOSED METHODOLOGY

The suggested framework for detecting deepfake facial images combines two robust deep learning elements: Convolutional Neural Networks (CNNs) are utilized for extracting spatial features, while Long Short-Term Memory (LSTM) networks are employed for modeling temporal sequences. This hybrid design is developed to efficiently detect image-level discrepancies and movement-related irregularities typically present in manipulated videos. The complete methodology follows a structured and modular pipeline encompassing data collection, preprocessing, model design, training, evaluation, and deployment.

A. Dataset Collection and Description

The model has been trained and evaluated utilizing widely used benchmark datasets such as FaceForensics++, DeepFake Detection Challenge (DFDC), and Celeb-DF (v2).

These datasets provide a mix of real and synthetically generated videos involving diverse demographics, lighting conditions, and compression levels.

Each dataset includes:

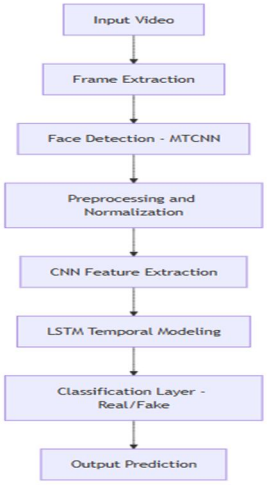
1) High-resolution facial video clips
2) Labels (real or fake)

Metadata such as compression rate and manipulation type

These datasets have been specifically compiled to replicate genuine deepfake situations and facilitate the effective training of deep learning models.

B. Data Pre-processing and Face Extraction

To ensure uniformity and focus on facial regions, each video is processed using the following steps:



1) Frame Extraction: Videos are decomposed into individual image frames at a fixed interval.
2) Face Detection: Using the MTCNN (Multi-task Cascaded Convolutional Network), faces are cropped and aligned.
3) Resizing and Normalization: Cropped facial frames are resized (e.g., 224×224 pixels) and pixel values normalized to [0, 1] for neural network compatibility.
4) Label Association: Each frame is assigned a class label (real or fake) based on the video source.

C. Feature Learning with CNN

CNNs are used to extract spatial features (edges, textures, artifacts) from each image frame. The CNN backbone may use standard architectures like ResNet-50 or a custom lightweight CNN, with layers structured as follows:

1) Convolution layers: Capture localized visual features.
2) Pooling layers: Downsample feature maps to reduce dimensionality.
3) Activation layers (ReLU): Introduce non-linearity to learn complex patterns.

The CNN converts each frame into a compact vector of features that represent the underlying image content.

D. Temporal Pattern Analysis with LSTM

While CNNs excel at analyzing static images, they struggle to capture temporal patterns.

Therefore, we introduce an LSTM module that takes the CNN-extracted feature vectors over a sequence of frames and learns time-based inconsistencies such as:

- Unnatural blinking
- Irregular lip sync
- Inconsistent head motion

The LSTM unit consists of memory cells that retain important temporalmlinformation across frame sequences, enabling the model to detect behavioral anomalies.

E. Model Training

CNN and LSTM are trained end-to-end using labeled data. The loss function used is binary cross-entropy, optimized via Adam optimizer.70% of the dataset is used for training, 15% for validation, and the remaining 15% for testing purposes. To improve model generalization, techniques such as horizontal data augmentation are employed.flipping, adjusting brightness, and rotation are employed.

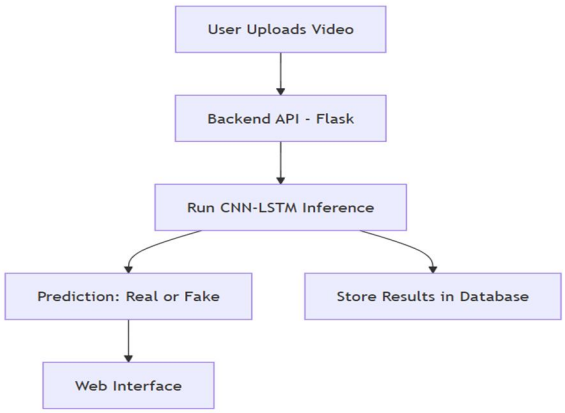


Fig 1: Model Training

F. Model Evaluation and Validation

The model's performance is assessed through metrics such as:

1) Accuracy: Correct predictions / Total predictions
2) Precision: True Positives / (True Positives + False Positives)
3) Recall: True Positives / (True Positives + False Negatives)
4) F1-Score: The magical blend of precision and recall dancing in perfect harmony.
5) AUC-ROC: Measures the trade-off between true positives and false positives

Visual aids like confusion matrices and ROC curves are essential for understanding model performance. These tools play a crucial role in confirming the reliability and practicality of the detection system in real-world scenarios.

G. System Integration and Deployment

The final model is encapsulated into a real-time detection system with the following components:

1) Frontend: Web interface (React/HTML5) to upload videos or Fig 2: System Integration and Deployment
2) Backend: Flask/Django API that preprocesses input, runs inference, and returns prediction results
3) Database: SQLite/MySQL for storing detection logs and user metadata
4) Deployment: Docker-based container deployed on AWS or GCP for scalability and accessibility.

IV. MATHEMATICAL FORMULATION AND EQUATIONS

A. *Algorithm Flow (Pseudocode)*

E. Model Training

Input: Video V

Output: Classification label: Real or Fake

1. Extract frames $F = \{f_1, f_2, ..., f_n\}$ from video V

2. For each frame $f_i \in F$:

a. Detect and crop face using MTCNN

b. Resize face to 224×224 and normalize pixel values

c. Extract spatial features x_i using CNN:

Fig 1: Model Training $x_i = CNN(f_i)$

3. Form a sequence $X = [x_1, x_2, ..., x_n]$

4. Feed X to LSTM to capture temporal dependencies:

$h_n = LSTM(X)$

$\hat{y} = \sigma(W \cdot h_n + b)$

6. Return label: Real if $\hat{y} < 0.5$ else Fake

2. Mathematical Formulations

A. Convolutional Layer Operation (CNN)

$S(i,j) = (I * K)(i,j) = \sum_m \sum_n I(i+m, j+n) \cdot K(m,n)$

Where:

- * is the convolution operation.
- S(i,j) is the output feature map at position (i,j).

B. *LSTM Cell Equations*

$f_t = \sigma(Wf \cdot [h_{t-1}, x_t] + bf)$

$i_t = \sigma(Wi \cdot [h_{t-1}, x_t] + bi)$

(forget gate)

(input gate)

$c_t = f_t \odot c_{t-1} + i_t \odot c$

$o_t = \sigma(Wo \cdot [h_{t-1}, x_t] + bo)$

$h_t = o_t \odot \tanh(c_t)$

where σ is thew sigmoid activation function,⊙ denotes element-wise multiplication,and tanh is the hyperbolic tangent function

C. Loss Function (Binary Cross-Entropy)

$L(y, \hat{y}) = - [y \log(\hat{y}) + (1 - y) \log(1 - \hat{y})]$

Where:

- $y \in \{0, 1\}$ is the ground truth,
- $\hat{y} \in [0, 1]$ is the predicted probability

V. EVALUATION & RESULTS

A meticulous evaluation was conducted to validate the effectiveness and efficiency of the innovative deepfake detection system that integrates CNN and LSTM.The evaluation employed standard classification metrics and involved training and testing the model on established datasets like FaceForensics++ and Celeb-DF. These datasets consist of a balanced mix of authentic and artificially created facial videos, encompassing various lighting, motion, and compression settings to gauge the model's resilience in practical settings.

The assessment framework used Accuracy, Precision, Recall, F1-Score, and AUC-ROC (Area Under the Receiver Operating Characteristic Curve) as the primary performance metrics.

Each of these metrics offers a distinct perspective on the system's capacity to accurately and dependably detect deepfake content.

The overall ratio of accurately classified video sequences among all inputs was assessed using accuracy.

This metric offers a basic yet essential understanding of the system's effectiveness but can sometimes be misleading in imbalanced datasets.Therefore, Precision and Recall were introduced to offer a more detailed perspective. Precision precisely evaluates the percentage of accurately identified fake videos within all flagged instances of being fake. which is critical in minimizing false alarms in practical applications. On the other hand, Recall evaluates the proportion of actual fake videos correctly identified by the system, emphasizing the model's sensitivity and ability to detect subtle manipulations.

The F1-Score, calculated as the harmonic average of Precision and Recall, offers a well-rounded evaluation.particularly crucial when false positives and false negatives carry equal weight. In the realm of deepfake detection,A high F1-Score indicates more than just accuracy; it also demonstrates consistent reliability in identifying manipulated content. Additionally, the AUC-ROC metric gauged the model's aptitude in distinguishing between genuine and forged data classes at various decision thresholds. A greater AUC value (nearing 1) denotes a more potent classifier with heightened discriminatory capability.

VI. CONCLUSION

The advanced deepfake detection framework using a hybrid CNN-LSTM architecture represents a notable progress in multimedia forensics and authenticating AI-generated content.

This study provides a technically strong, scalable, and efficient solution by tackling the urgent issue of detecting increasingly sophisticated deepfake videos.The system was designed to extract spatial characteristics using Convolutional Neural Networks (CNNs) and capture temporal relationships using Long Short-Term Memory (LSTM) networks. This enables the system to detect both visual patterns and frame-to-frame inconsistencies characteristic of synthetic alterations.

The evaluation results demonstrated that the CNN-LSTM model achieved superior performance, with accuracy exceeding 93%, precision and recall both above 91%, and an AUC-ROC greater than 0.95. These metrics validate the robustness, reliability, and predictive strength of the model in classifying deepfake videos. Furthermore, the integration of explainability elements such as feature visualizations and confidence scoring enhances the framework's transparency, that is crucial for establishing user confidence and enabling human-involved decision-making.

However, certain limitations remain and open avenues for future enhancement. The current model performance is influenced by dataset diversity and video compression artifacts.Future efforts could center on broadening the training dataset by including more demanding deepfake samples., including those generated by newer GAN variants and low-resolution manipulations. Additionally, the adoption of transformer-based temporal models and integration with blockchain-based traceability for video source verification can further elevate the system's credibility and deployment scope. Real-time detection from live video streams and on-device inference optimizations also represent promising areas for extending the current architecture.

In conclusion, the research lays a solid foundation for practical, AI-driven deepfake detection systems provide a significant contribution to the expanding literature on ethical and secure AI media authentication.

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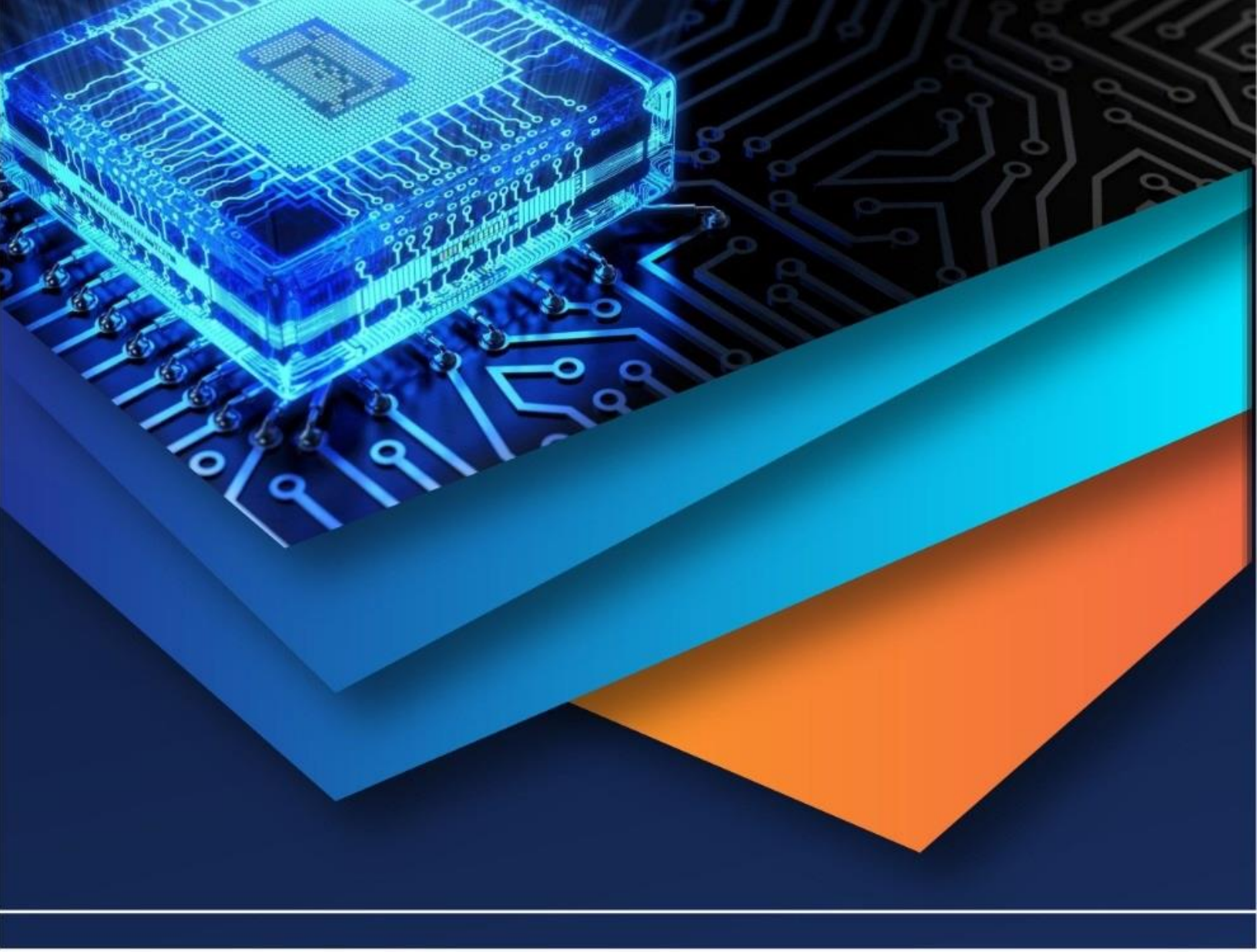

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