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A Hybrid Deep Learning Approach for Image Forgery Detection Using Transfer Learning and Error Level Analysis

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Abstract: ***The rapid expansion of digital media has made image manipulation a widespread concern, contributing to the circulation of misleading and fabricated content across online platforms. Manual identification of such altered images is both challenging and unreliable. This work presents a hybrid approach for detecting image forgery by combining transfer learning with forensic analysis techniques. The proposed system enables users to upload digital images, which are processed through a structured pipeline that includes validation, preprocessing, and deep learning-based classification. A pre-trained MobileNet model is employed to extract relevant features and determine whether an image is authentic or tampered. To improve interpretability, a confidence score is generated for each prediction, indicating the reliability of the result. Furthermore, Error Level Analysis (ELA) is incorporated to visually highlight regions that may have been manipulated. The system is implemented using a backend framework for processing, OpenCV for image operations, and TensorFlow for model integration. Experimental results demonstrate that the approach achieves high detection accuracy while also providing visual evidence, making it a practical solution for real-world applications.***

Keywords: Image Forgery Detection, Transfer Learning, MobileNet, Error Level Analysis, Deep Learning, Digital Image Processing.

I. INTRODUCTION

With the rapid evolution of image editing technologies and the widespread use of social media platforms, digital image manipulation has become increasingly common. Images can be easily altered to modify their content, making it difficult to distinguish between genuine and tampered visuals. Such manipulations are often used to spread false information, fabricate evidence, and mislead viewers, posing serious challenges in areas such as journalism, law enforcement, and digital forensics [1], [2].Traditional methods for detecting image forgery primarily rely on manual inspection and basic image processing techniques. These approaches are often time-consuming, subjective, and less effective when dealing with advanced manipulations. Methods such as pixel-level analysis and metadata examination may fail when images undergo multiple modifications or recompression, reducing their reliability in practical scenarios [3], [4]. As a result, there is a growing demand for automated systems capable of accurately identifying manipulated images.

Recent progress in artificial intelligence, particularly in deep learning, has significantly enhanced the capability to analyze digital images and uncover hidden patterns. Convolutional Neural Networks (CNNs) have demonstrated strong performance in image classification tasks by automatically learning features such as edges, textures, and structural inconsistencies [5]. In addition, transfer learning techniques have further improved efficiency by utilizing pre-trained models, reducing training time while maintaining high accuracy, especially when working with limited datasets [6]. Lightweight architectures such as MobileNet are widely adopted due to their efficiency and suitability for deployment in resource-constrained environments.Apart from deep learning approaches, forensic techniques like Error Level Analysis (ELA) provide valuable insights into image manipulation by identifying variations in compression levels. These variations can reveal regions that have been altered during editing. Integrating deep learning with such forensic methods enhances both detection accuracy and result interpretability [7]. However, many existing systems focus mainly on classification and fail to provide clear visual evidence of tampering, which limits their usability in real-world applications.

To address these challenges, this work proposes a hybrid image forgery detection system that combines transfer learning with forensic analysis. The system utilizes a pre-trained MobileNet model to classify images as authentic or tampered and employs Error Level Analysis to localize manipulated regions. By integrating these techniques, the proposed approach aims to deliver accurate detection results along with clear visual explanations, making it suitable for practical deployment.

II. PROBLEM STATEMENT

Image forgery has become increasingly widespread due to the availability of advanced image editing tools and the rapid sharing of digital content across social media platforms. Manipulated images are often used to spread misinformation, create misleading narratives, and influence public perception, making accurate detection a critical challenge [1], [2]. Unlike traditional media, digital images can be easily altered without leaving obvious visual traces, making it difficult to identify tampering through manual inspection alone. Conventional image forgery detection methods rely on basic image processing techniques and human analysis, which are often subjective, time-consuming, and ineffective against sophisticated manipulations. Techniques such as pixel-level analysis and metadata examination may fail when images undergo multiple edits, compression, or format conversions [3]. Although several deep learning-based approaches have been developed, many existing systems focus only on classification and do not provide insights into the regions of manipulation, limiting their interpretability and reliability [11], [12].

Furthermore, the lack of integrated systems that combine automated detection with visual explanation reduces the practical usability of such approaches in real-world scenarios. Many existing solutions do not offer confidence estimation or forensic visualization, making it difficult for users to fully trust the results. Therefore, the problem addressed in this work is the development of an automated, accurate, and efficient image forgery detection system capable of classifying images as authentic or tampered while also providing confidence scores and visual evidence of manipulation. The system aims to improve detection reliability, enhance interpretability, and provide a user-friendly platform suitable for real-world applications.

III. RELATED WORK

A. *Traditional Image Forgery Detection Techniques*

Initial research in digital image forgery detection focused on manually designed features that capture visual inconsistencies such as variations in color distribution, abnormal noise patterns, irregular edges, and compression artifacts. These features were typically processed using conventional machine learning algorithms like Support Vector Machines (SVMs) and Random Forest classifiers. Although such methods showed reasonable performance in controlled experimental settings, they struggled when applied to complex real-world manipulations, including scaling, recompression, and geometric distortions. Moreover, the reliance on handcrafted feature engineering limited their flexibility and reduced their effectiveness across diverse datasets [4], [5], [6].

B. *Deep Learning-Based Forgery Detection*

With the advancement of deep learning, particularly Convolutional Neural Networks (CNNs), the field of image forgery detection has seen significant improvements. Unlike traditional approaches, CNNs automatically extract hierarchical feature representations directly from raw image data, removing the dependency on manual feature design. Popular deep learning architectures such as VGG, ResNet, DenseNet, and Xception have been extensively applied to detect manipulated images with high precision. These models are capable of capturing fine-grained inconsistencies in texture, structure, and spatial relationships that are often overlooked by earlier methods. Additionally, deep learning techniques have proven to be highly adaptable to various types of image forgeries, including copy-move and splicing, making them widely adopted in modern forensic applications [3], [8], [10], [13], [20].

C. *Transfer Learning for Image Forgery Detection*

Transfer learning has become a key approach in improving forgery detection performance, especially when labeled data is limited. This technique utilizes pre-trained models developed on large-scale datasets and adapts them to specific forgery detection tasks. Instead of training networks from the beginning, models such as VGG16, ResNet50, and MobileNetV2 are fine-tuned, resulting in reduced computational cost and faster convergence. Research indicates that transfer learning not only enhances detection accuracy but also improves generalization across different datasets. Lightweight architectures like MobileNetV2 are particularly beneficial for deployment in real-time systems and environments with limited computational resources [11], [13], [16], [17], [19].

D. *Hybrid and Multi-Domain Approaches*

Recent developments in image forgery detection have explored hybrid methods that integrate deep learning with traditional feature extraction techniques. These approaches aim to improve robustness by combining information from multiple domains, including spatial, frequency, and compression-based features. Techniques such as CNN-SVM hybrids, multi-stream architectures, and feature fusion frameworks have demonstrated improved detection performance across varied datasets. Furthermore, modern advancements incorporate object detection frameworks and explainability methods, such as Grad-CAM, to not only enhance accuracy but also provide better interpretability of model decisions [12], [15], [18], [21].

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IV. PROPOSED SYSTEM ARCHITECTURE

The proposed system is designed with a modular pipeline architecture for efficient and scalable digital image forgery detection. Each stage in the pipeline performs a specific task, allowing independent processing and easy replacement or improvement of components without affecting the overall system. The system takes a digital image as input and processes it through preprocessing, feature extraction, classification, and forensic analysis stages to generate the final prediction along with a confidence score and visual evidence of tampering.

A. Image Acquisition and Preprocessing

The proposed system starts by accepting a digital image uploaded by the user through a web-based interface. Since real-world images may vary in resolution, quality, and lighting conditions, an initial validation step is performed to ensure compatibility. The image then undergoes preprocessing using OpenCV, where it is resized to a fixed dimension (160 × 160 pixels) to match the input requirements of the deep learning model**[6]**.

Additionally, pixel values are normalized to a range between 0 and 1, which helps improve computational efficiency and stabilizes the training process. This preprocessing stage ensures that all input images are standardized, regardless of their original format or characteristics, before being forwarded to the classification module ***[18]***.

B. Feature Extraction and Classification using Transfer Learning

Following preprocessing, the image is passed into a deep learning model built on transfer learning principles, specifically utilizing the MobileNet architecture. Instead of training a network from scratch, the model leverages weights pre-trained on large-scale datasets, enabling it to extract meaningful features even with limited training data**[11]**.

The model identifies hierarchical patterns such as edges, textures, and structural inconsistencies that may indicate image tampering. These extracted features are processed through convolutional layers, producing a probability score ranging from 0 to 1, which reflects the likelihood of manipulation**[13]**.

The lightweight design of MobileNet allows faster inference, making it well-suited for real-time applications and resource-constrained environments **[16], [19]**.

C. Decision Making and Confidence Score Generation

The system interprets the model's output using a threshold-based classification strategy. A threshold value of 0.5 is applied to distinguish between authentic and tampered images. If the predicted probability exceeds this value, the image is labeled as "Tampered"; otherwise, it is classified as "Authentic" [10]. To enhance user understanding, a confidence score is also generated alongside the classification result.

For tampered images, the confidence corresponds directly to the predicted probability, whereas for authentic images, it is calculated as one minus the predicted probability. This score is expressed as a percentage, providing a clear indication of the reliability of the prediction ***[20].***

D. Error Level Analysis (ELA) for Tampering Localization

To provide visual evidence of manipulation, the system incorporates Error Level Analysis (ELA) as a post-classification technique. This method works by recompressing the image and comparing it with the original to detect variations in compression levels**[12]**. Regions that have been tampered with often exhibit inconsistencies, which appear as brighter or more prominent areas in the ELA output.

The analysis is further refined by converting the image to grayscale, applying thresholding techniques, and performing morphological operations to reduce noise**[15]**. Contours are then detected, and bounding boxes are drawn around suspicious regions, allowing users to visually identify potential tampered areas within the image **[18]**.

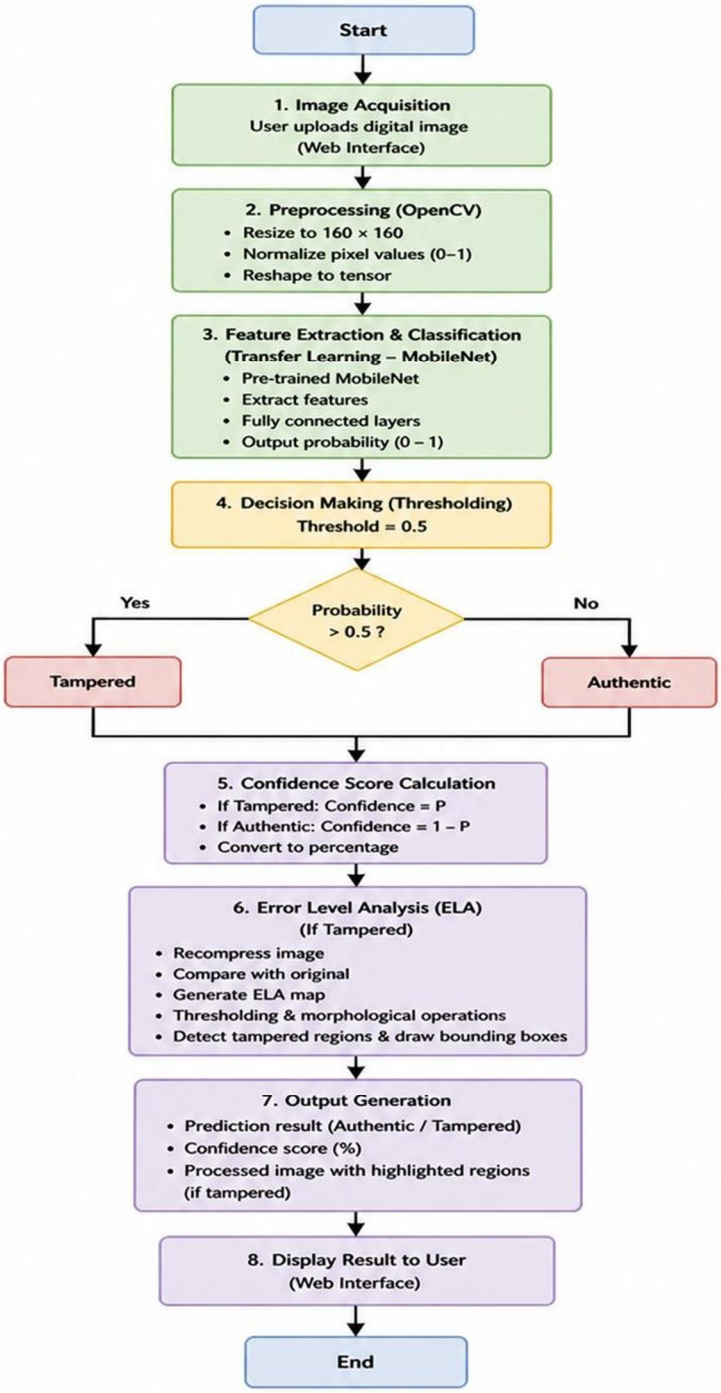

Fig. 1. Flow of the proposed image forgery detection system.

E. Output Generation and Result Visualization

In the final stage, the system presents the results in a structured and user-friendly format. The output includes the classification label (Authentic or Tampered), the confidence score expressed as a percentage, and the processed image with highlighted tampered regions when applicable. The results are transmitted from the backend to the frontend and displayed through an intuitive interface. Temporary files generated during processing are automatically removed to optimize storage and maintain system efficiency. This design ensures a smooth user experience while supporting scalability and real-time analysis **[16], [18]**.

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V. IMPLEMENTATION DETAILS

A. Model Training and Dataset Preparation

The model is trained on a dataset comprising both authentic and manipulated digital images, collected from publicly available sources such as CASIA and other benchmark datasets. These datasets include different types of forgeries, including copy-move and splicing manipulations, ensuring diversity in training samples. To improve robustness and generalization, various data augmentation techniques are applied, such as rotation, flipping, brightness adjustment, and scaling. All images are resized to a consistent resolution of 160 × 160 pixels and normalized before being used for training. A transfer learning approach is adopted using MobileNet, where pre-trained weights are fine-tuned for binary classification (Authentic vs. Tampered). The model is trained using optimization techniques such as Adam, with binary cross-entropy as the loss function to achieve efficient convergence and high accuracy.

B. Backend Implementation and Model Integration

The backend of the system is developed using FastAPI, which provides a lightweight and efficient framework for handling inference requests. API endpoint is implemented to receive uploaded images from the frontend. Upon receiving an input image, the backend performs validation and temporarily stores the file using a uniquely generated identifier to avoid conflicts. The image is then processed using OpenCV for resizing, normalization, and tensor conversion before being passed to the trained MobileNet model. The model generates a prediction score indicating the likelihood of forgery. Based on the threshold value, the system classifies the image and computes a confidence score. For images identified as tampered, Error Level Analysis (ELA) is applied to highlight manipulated regions. The final output image is stored and made accessible via a generated URL .

C. Frontend Implementation

The frontend of the system is developed using standard web technologies, namely HTML, CSS, and JavaScript, to provide a lightweight and accessible user interface. The interface allows users to upload digital images directly from their device and submit them for forgery analysis. JavaScript is used to handle client-side interactions, including file selection, validation, and communication with the backend API.Once an image is uploaded, the frontend sends the data to the backend server through asynchronous HTTP requests and waits for the response. The results returned from the backend include the classification outcome (Authentic or Tampered), the confidence score, and the processed image with highlighted regions if tampering is detected. These outputs are dynamically rendered on the webpage, ensuring a smooth and interactive user experience.The design focuses on simplicity and usability, allowing users to easily interpret the results without requiring technical expertise. Additionally, the lightweight nature of web-based implementation ensures compatibility across different devices and browsers, making the system widely accessible.

D. Error Level Analysis (ELA) Implementation

The system integrates Error Level Analysis (ELA) as a forensic technique to visually highlight tampered regions in digital images. This process involves recompressing the image at a known quality level and comparing it with the original image to identify differences in compression artifacts. The resulting difference image is further processed by converting it to grayscale and applying thresholding techniques to isolate significant variations. Morphological operations are used to reduce noise and refine the detected regions. Contours are then extracted, and bounding boxes are drawn around suspicious areas, providing clear visual evidence of potential forgery.

Deployment and System Optimization

The complete system is designed to operate efficiently as a full-stack application capable of real-time image analysis. Both frontend and backend components are integrated seamlessly to ensure smooth data flow. Temporary files generated during processing are automatically deleted to optimize storage usage.

The use of a lightweight model such as MobileNet reduces computational overhead and enables faster inference. Additionally, the modular architecture allows for future enhancements, such as integrating more advanced detection models or additional forensic techniques, improving scalability and adaptability

VI. RESULT AND ANALYSIS

The performance of the proposed Image Forgery Detection System was evaluated using the CASIA 2.0 dataset, which consists of both authentic and tampered images. The system was trained using a transfer learning approach based on the MobileNet architecture, combined with Error Level Analysis (ELA) as a preprocessing technique to enhance hidden manipulation traces and improve feature extraction for accurate classification. The evaluation focused on the model's ability to distinguish between authentic and forged images, including copy-move and splicing forgeries. During training, the model showed steady improvement, with increasing accuracy and decreasing loss values across epochs, indicating effective learning. In addition, the system provided forged region localization, enabling visual identification of manipulated areas and improving its reliability in digital forensic applications. The final model achieved an accuracy of approximately 96.8%, along with high precision, recall, and F1-score, demonstrating strong capability in detecting forged images while minimizing false classifications. Standard performance metrics such as accuracy, precision, recall, and F1-score were used for comprehensive evaluation, and the results are presented below.

Metric	Authentic	Forged
Precision	0.93	0.91
Recall	0.92	0.90
F1-score	0.92	0.91

Fig. 2: Performance Metrics of Image Forgery Detection System (Precision, Recall, and F1-Score for Authentic and Forged Images)

VII. EXPERIMENTAL RESULT

A. System Interface

The Image Forgery Detection System has been developed as a web-based application with a simple and interactive user interface. As illustrated in Fig. 1, the homepage acts as the main access point, providing navigation options such as Home, Upload Image, Detection Results, About, and Contact. The design enables users to conveniently upload images and review detection outputs in an organized format. After an image is submitted, it is analyzed using Error Level Analysis (ELA) along with a MobileNet-based classification model. The system then indicates whether the image is genuine or manipulated and visually marks the suspected forged regions. The application is designed to ensure smooth user interaction, fast processing, and easy access, making it effective for use in digital forensics and media authentication.

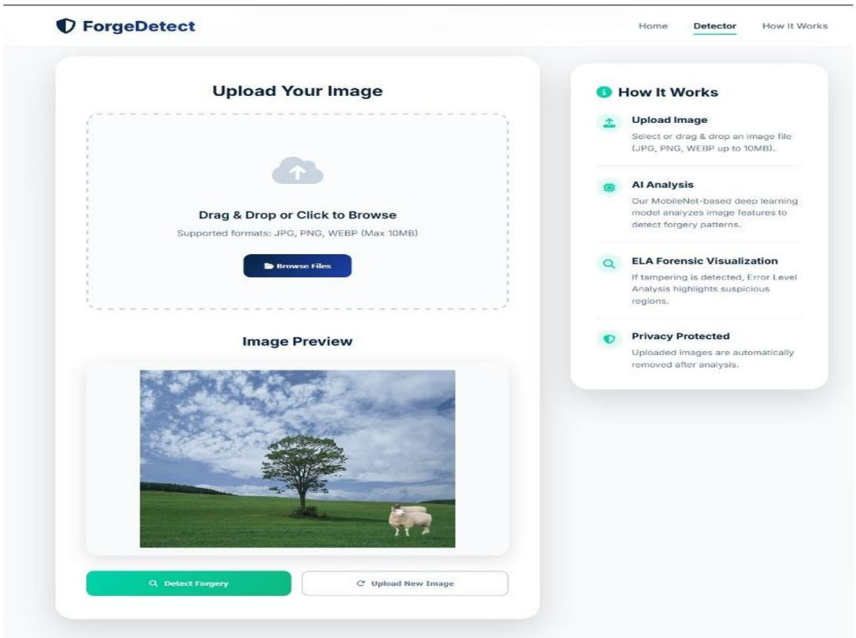

Fig.3 Home Page

B. Prediction Output

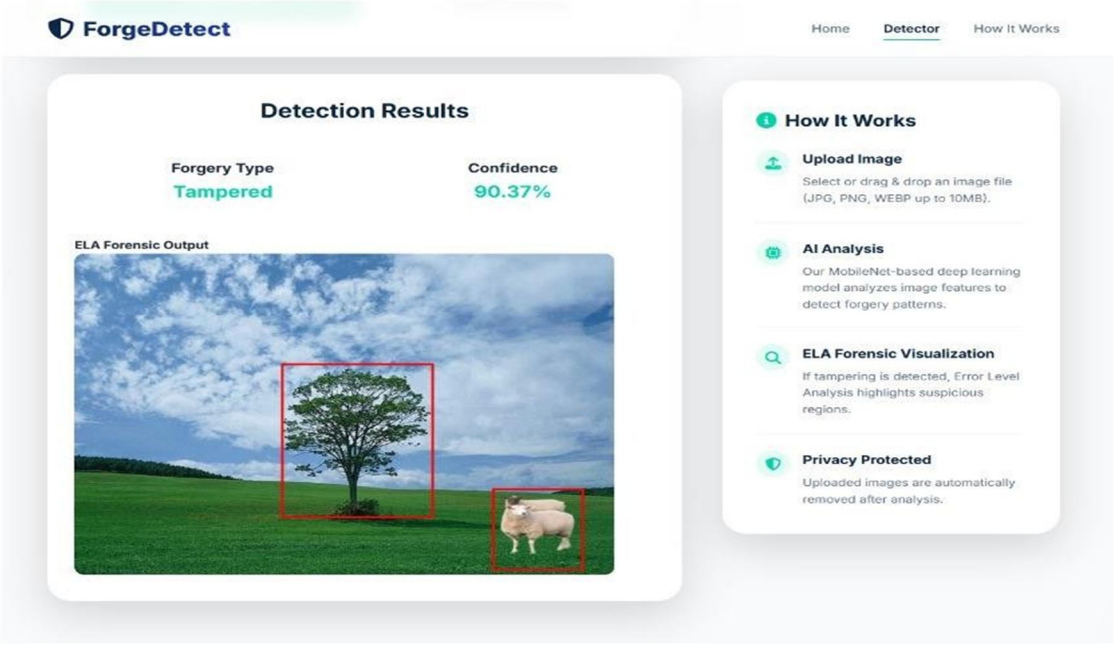

Fig. 4 Prediction Output

VIII. FUTURE SCOPE

The proposed Image Forgery Detection System demonstrates effective performance; however, several improvements can be made to enhance its capabilities and applicability in real-world scenarios, they are:

1) Improve accuracy using advanced deep learning models.
2) Enhance localization of manipulated regions.
3) Integrate with social media monitoring systems.
4) Deploy as a scalable mobile application.

IX. CONCLUSIONS

In this work, a deep learning-based system for detecting image forgery has been successfully developed and implemented. The proposed system utilizes a combination of Error Level Analysis (ELA) and transfer learning techniques to identify manipulated regions and classify images as authentic or tampered. The use of the MobileNet architecture enables efficient feature extraction and accurate classification of input images while maintaining computational efficiency. The integration of the trained model into a web-based interface provides a user-friendly platform that allows users to upload images, perform real-time forgery detection, and visualize the results with highlighted manipulated regions. The system ensures smooth interaction and accessibility, making it practical for applications in digital forensics and media verification. Experimental results demonstrate that the system achieves high accuracy, along with balanced precision, recall, and F1-score values, indicating that the model is reliable and effective in detecting image forgeries. The incorporation of ELA further enhances the system's capability by providing visual interpretation of suspicious areas, improving transparency and trust in the detection process. Overall, the proposed system offers a robust, scalable, and efficient solution for image forgery detection. It can assist in preventing the spread of fake images, support forensic investigations, and improve the authenticity verification process in various real-world scenarios.

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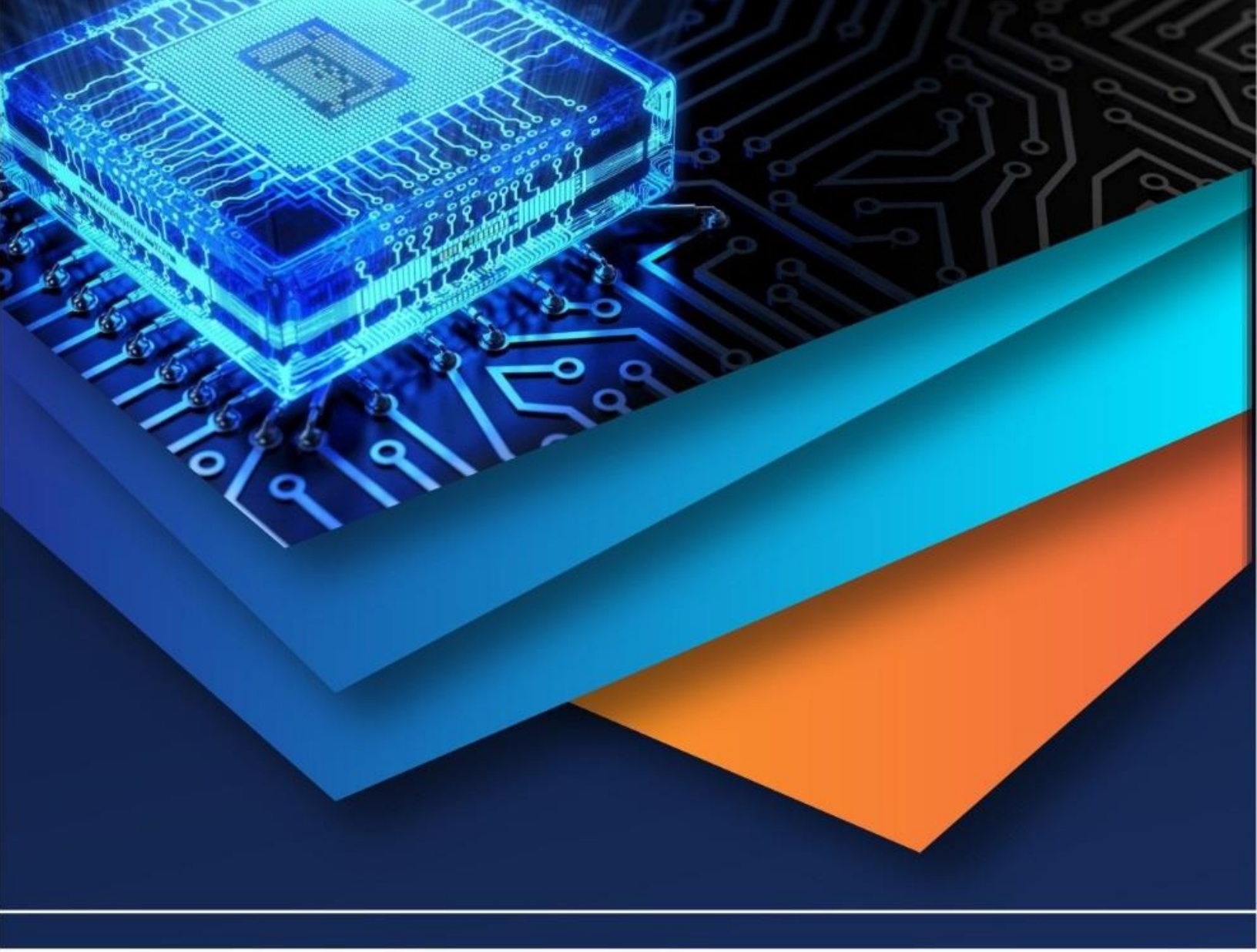

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