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Leveraging ResNet and U-Net Architectures for Accurate Image Forgery Detection and Localization: A Comprehensive Survey

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Abstract: The area of image forgery localization and detection (IFDL) has received considerable attention because of the increased manipulations in the digital age facilitated by powerful generative AI technology. This survey focuses on recent trends in deep learning techniques, especially multimodal, explainable, and generalizable models built up to 2025. U-Net variants and transformer-based models are the main developments, focusing on forgery trace detection. Deep learning models, especially ResNet and U-Net, have improved image forgery detection and localization due to better feature extraction and semantic segmentation. The review incorporates state-of-the-art approaches employing these models and carries out a critical appraisal of design, evaluation metrics, limitations, and possible extensions. The FakeShield framework brings in a trend change by embracing multi-modal LLMs for explainable detection and localization. New approaches like MMTD-Set have provided a greater cross-domain adaptability during model training. Complementary studies investigate novel paradigms to enhance localization accuracy and robustness against anti-forensic attacks. In-depth analyses emphasize the use of complementary forensic analyses when considering real-life scenarios. This survey is a complete guide for research and practitioners working on designing next-generation image forgery detection systems that are accurate yet explainable.
Keywords: Image forgery localization and detection; Deep learning; U-Net; ResNet; MMTD-Set

I. INTRODUCTION

Digital image forgery has spiked with the advancements in image manipulation software and generative models, resulting in higher-level manipulation that are tougher to detect. The authenticity of visual information matters in sectors like journalism, law enforcement, and social media platforms, where faked images may sway public perceptions and judicial outcomes [1] [2]. For this reason, the establishment of machine learning-based accurate, interpretable, and automation-enabled forgery detection and localization schemes is crucial. It was introduced a better Mask R-CNN model for image forgery detection and localization [3]. The authors extend the original Mask R-CNN structure to better capture forgery details, and thus it has high accuracy in detecting manipulated regions.

Among various deep learning architectures, Residual Networks (ResNet) and U-Net gained prominence since they are capable of learning deep hierarchical representations and performing accurate pixel-level segmentation respectively. ResNet's residual connections help mitigate vanishing gradient problems in deep networks to enable effective feature extraction for classification purposes [4] [5]. U-Net, initially designed for biomedical segmentation, excels in identifying changed regions in images by including encoder-decoder models as well as skip connect [4] [5].

This survey integrates recent advancement using only ResNet and U-Net architectures in image forgery localization and detection with concern for methodological innovations, benchmarking tests, and utility of deployment. The reviewed literature extends from simple architectures to complex models that include ResNet encoders within U-Net architectures, transfer learning technology, and federated learning mechanisms for decentralized detection [6] give an introduction of deep learning techniques applied to image forgery detection, touching on various architectures and their performance in identifying doctored images. [7] Discusses the use of deep learning techniques for digital image forgery detection, with a focus on the benefits of CNNs in identifying manipulation artifacts.

Deep learning has transformed image forensic analysis by facilitating automatic feature extraction and large-scale end-to-end training. ResNet architectures produce deep feature hierarchies via residual connections, countering degradation problems in extremely deep networks. U-Net, which was initially designed for biomedical image segmentation, presents an efficient encoder-decoder design with skip connections to maintain spatial context, a requirement for accurate forgery localization.

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II. DEEP LEARNING ARCHITECTURES IN IMAGE FORGERY DETECTION

A. Residual Network (ResNet)

ResNet structures provide identity shortcut connections to allow very deep neural networks to be trained without a drop in accuracy, a big improvement for image classification tasks. In the case of image forgery detection, ResNet variants like ResNet-50 have been used widely for their deep feature extraction capabilities.

1) Applications and Variants: [4] used ResNet-50 in a federated learning setup to improve face forgery detection in decentralized datasets, showing enhanced generalizability and privacy protection. [8] Used ResNet-50 for detecting copy-move forgery, showing enhanced accuracy because of the network's ability to detect subtle manipulation features.
2) Hybrid Models: ResNet encoders have been integrated into U-Net models to leverage classification power along with accurate localization. [9] Introduced TASPP-UNet, which uses a pre-trained ResNet-50 encoder with atrous convolution blocks, demonstrating better segmentation performance in polyp detection, a technique that can be translated to forgery localization tasks.
3) Performance Benchmarks: [10] documented that ResNet50-based models achieve detection accuracies of more than 95% on benchmark datasets like CASIA and MICC-F220, which testify to the architecture's strength in extracting discriminative features from spoofed images.

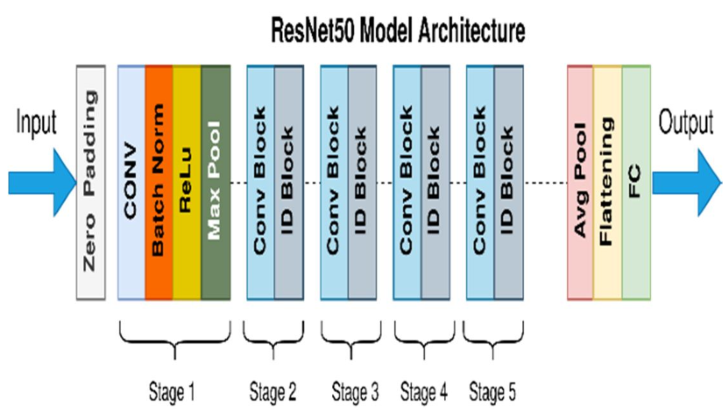

Fig.1 ResNet Architecture

B. U-NET and its Variants

U-Net's encoder-decoder architecture with skip connections supports efficient semantic segmentation necessary for localizing forgery areas in images. [11] Suggest a U-Net-based architecture optimized with a grasshopper optimization algorithm to identify social media image forgeries. The method enhances detection efficacy by efficiently searching through the search space to find optimal parameters. [12] Proposes a Dense U-Net model that includes cross-layer intersections to enhance feature propagation and improve detection and localization of image forgery. The proposed architecture demonstrates remarkable performance improvements in terms of metrics [13] introduces an improved two-way U-Net model specifically tailored for detecting copy-move forgery. The authors prove that their method is effective in detecting duplicated areas with better accuracy. [14] Introduce RRU-Net, wherein ringed residual connections are incorporated in the U-Net architecture to better detect splicing forgeries by efficiently capturing residual artifacts.

- Key Contributions: [5] showed the effectiveness of enhanced U-Net models paired with error level analysis for accurate image forgery localization. [12] Proposed U2-Net, a two-level nested version of U-Net, enhancing detection granularity by extracting multi-scale contextual information.
- Hybrid and Attention-Augmented Models: [15] created a Circular U-Net with attention gates that prioritize salient tampered areas at segmentation time for better detection precision for splicing forgeries. *[16]* Introduced UCM-Net, a U-Net-like network specifically designed for copy-move forgery detection with tampered-region-related features added for improved robustness.
- Benchmark Performance: [17] pioneered a new U-Net variant with better localization performance on various datasets such as CASIA2 and MICC-F220, highlighting the flexibility of U-Net architectures in handling various forgery types.

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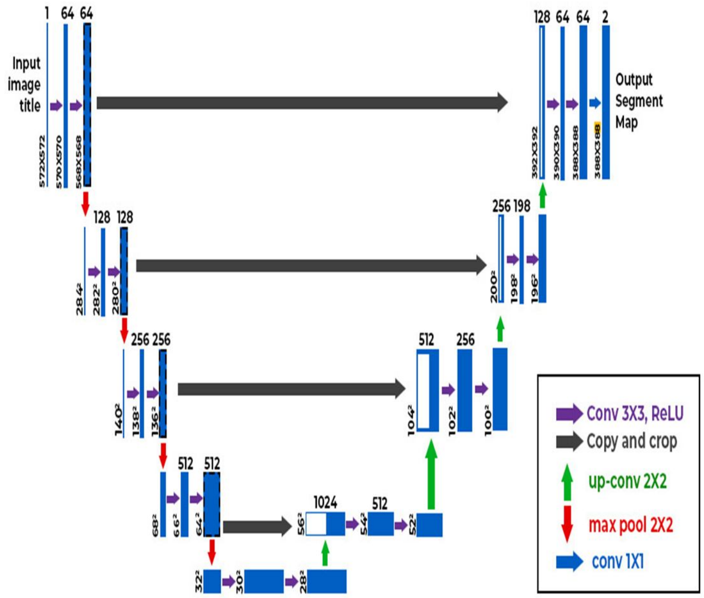

Fig.2 U-Net Architecture

C. Hybrid U-Net With Resnet Encoders

The integration of ResNet's feature extraction and U-Net's segmentation abilities has emerged as a prevailing standard.

- [17] Presents a hybrid model of U-Net using VGG16 as a feature extraction network paired with a residual-modified U-Net for segmentation and classification. Their method achieved better performance on the CASIA2 dataset than state-of-the-art approaches, with robustness and efficiency ideal for real-world use.
- [18] Introduces a hierarchical progressive detection model based on U-Net, incorporating ResNet backbones, allowing multi-level feature exploitation for improved detection and accurate localization. [19] Highlights the significance of context retrieval towards detecting forgery. The authors introduce an approach that examines contextual data to improve forgery detection accuracy and localization, evidencing the power of context-aware methods.

D. Ringed Residual U-Net (RRU-Net)

Ringed Residual U-Net (RRU-Net) is a deep learning model created to combat the increasing problem of image splicing forgery, a type of digital image tampering that has become increasingly prevalent with readily available editing software. RRU-Net is unique in its end-to-end segmentation ability, which enables it to identify forgeries from input images directly without any preprocessing or post-processing procedures. This simplifies the detection pipeline and improves usability in practical applications.

Inspirited by human cognitive mechanisms, especially how the brain remembers and consolidates information, RRU-Net improves the depth of learning of Convolutional Neural Networks (CNNs). This cognitive method improves the model's capacity to extract and retain key image features that are essential in identifying genuine and tampered areas.

The architecture's central strength is the three inter-related mechanisms. Residual Propagation first assists in preserving and passing on significant features across the network layers, fixing problems such as vanishing gradients. Residual Feedback secondly aggregates learned features and employs an attention mechanism to emphasize discriminative areas, enhancing the model's sensitivity to tampered regions. Lastly, the Ringed Residual Structure combines both the propagation and feedback in a cyclic structure, consolidating the learning of key image features and guaranteeing strong and consistent performance.

Experimental results indicate that RRU-Net performs better than state-of-the-art techniques in important metrics like precision, recall, and F-measure, validating its efficacy. Overall, RRU-Net is a major contribution to image forensics by combining cognitive inspiration with strong network design, and it is a solid foundation for future work and real-world forgery detection tools.

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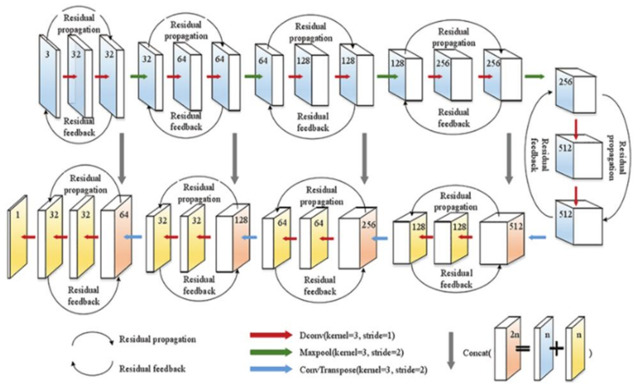

Fig.3 RRU-Net Architecture

E. Residual Transformer (ResTran)

ResTran (Residual Transformer) is a deep learning architecture for image forgery detection, especially for sophisticated manipulations such as splicing and copy-move forgery. It does this by integrating two strong architectures: ResNet, which learns rich and detailed local features from images, and a Transformer decoder, which learns global dependencies and patterns in the whole image. This integration enables ResTran to detect subtle and spatially separated tampered areas that may not be detected by standard CNN-based approaches.

One of ResTran's strongest aspects is its multi-tampering detection ability, that is, to detect and locate various kinds of forgeries simultaneously. This is particularly useful in real-world image forensics, where tampering methods tend to be used in combination with each other.

The model structure is composed of a ResNet backbone for feature extraction, followed by feature serialization to preprocess the data for the Transformer, and finally a Transformer encoder layer that applies self-attention to learn spatial relations. The design allows ResTran to achieve a balance between local details and global context, enhancing detection accuracy.

ResTran was tested on benchmark datasets like CASIA, NIST, and IMD2020 and performed robustly consistently across all of them, particularly when it came to identifying splicing-type forgery. Its strong performance and robust results show the potential of this model as a sound solution to real-world tasks of image forgery detection.

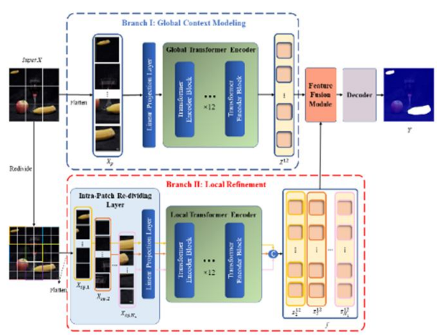

Fig.4 Image Copy–Move Forgery Detection

III. A THOROUGH RIVIEW ON IMAGE FORGERY DETECTION AND LOCALIZATION

A. Classification And Localization Paradigms

Image forgery detection systems usually consist of two fundamental tasks: detection (binary classification of genuine vs. forged images) and localization (detection of exact manipulated areas).

1) Classification: ResNet architectures are superior in binary classification of images using deep hierarchical feature extraction, allowing detection of minor inconsistencies caused by forgery [1] [2]
2) Localization: U-Net driven models conduct pixel-level segmentation to localize manipulated regions in images, which is crucial in forensic investigations and legal evidence [5] [6]

Hybrid models tend to combine these operations and include classification heads with segmentation decoders to optimize forgery detection as well as localization together [17] [18] Encoder-decoder models have been extensively applied to pixel-level forgery localization. They are, however, challenged by scale variation of forgery areas, typically constrained by fixed patch sizes and inadequate incorporation of global context. Hybrid models that integrate CNNs with LSTMs (e.g., H-LSTM, J-LSTM) improve boundary detection but are challenged by higher computational costs due to patch-wise processing.

B. Transfer Learning And Pretraining

To overcome labeled forgery dataset scarcity, transfer learning from pre-trained ResNet encoders on extensive image datasets (e.g., ImageNet) has become popular. [20] Showed that transfer learning remarkably improves detection accuracy and training efficiency, especially when fine-tuned over domain-specific forgery datasets. [9] Applied pre-trained ResNet-50 weights over U-Net structures along with atrous convolution blocks for effective feature extraction without significant retraining. Transformers have transformed numerous vision tasks, including forgery localization. Models like AdaIFL (ECCV 2024) and TBFormer (SPL 2023) utilize attention mechanisms to dynamically attend to significant areas, enhancing localization robustness at various scales.

C. Federated Learning Strategies

Federated learning facilitates decentralized model training on various devices or institutions without exposing sensitive image data, maintaining privacy. [4] Applied a federated learning approach using ResNet for face forgery detection with competitive accuracy while maintaining data privacy and adhering to data protection laws.

D. Error Level Analysis And Edge Detection Integration

Classical forensic indicators like error level analysis (ELA) and edge detection have been combined with deep learning models for improved detection. [5]

Used ELA as a preprocessing step for U-Net architectures, enhancing detection sensitivity for compression artifacts pointing towards forgery. [21] Combined edge detectors with deep learning to strengthen boundary definition of spliced areas.

IV. BENCHMARK DATASETS AND EVALUATION METRICS

A. Benchmark Datasets

[22] Discusses the notion of image provenance and its application in forgery detection. The authors use large datasets to understand where images come from and how information on provenance can be used to detect forgeries.

- CASIA Image Tampering Detection Dataset (v2.0): Comprises 10,000 images with different manipulations, commonly utilized for training and testing forgery detection models [17] [1]
- MICC-F220 Dataset: Utilized for testing segmentation and classification techniques, especially in copy-move forgery detection [2]
- FaceForensics++: Utilized in face forgery detection, specifically for testing deepfake and face swapping detection models based on ResNet and U-Net backbones [4]

TABLE 1: Benchmark Dataset Characteristics For Image Forgery Detection

Dataset	Forgery Types	Size (Images)	Annotations Type
CASIA2	Copy-move, Splicing	~7,491	Pixel-level masks
CoMoFoD	Copy-move	~1,800	Forgery masks
Columbia	Splicing	~180	Forgery masks
FFHQ (DeepFake)	Face manipulation	~70,000	Face landmarks
MMTD-Set	Multi-modal forgeries	34,000+	Multi-modal masks

Source [23] [14]

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B. *Evaluation Metrics*

- Accuracy, Precision, Recall, F1-Score: Typical classification metrics used to measure detection performance[1] [2]
- Intersection over Union (IoU) and Dice Coefficient: Measures of segmentation accuracy and localization precision [5] [24]
- Robustness Tests: Testing under different compression levels, post-processing noise, and adversarial perturbations to evaluate real-world usability. [8] [17]

Table 2: Comparative Performance of ResNet and U-Net Based Models on CASIA2 Dataset

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
ResNet-50 + RF Classifier	97.5	96.2	95.8	96.0
U-Net (Standard)	95.8	93.5	94.0	93.7
RRU-Net	98.2	97.3	96.8	97.0
ResTran	85.6	81.9	84.7	68.9

Source: [25] [14]

Table 3: Post-Processing Robustness Evaluation on CoMoFoD Dataset (F1 Scores)

Post-Processing Techniques	U-Net (%)	RRU-Net (%)	Fake Shield (%)	ResTran (%)
Brightness Change	88.7	90.3	93.2	92.5
JPEG Compression	85.2	88.7	91.7	91.0
Noise Addition	83.9	86.3	90.1	89.7
Image Blurring	80.1	83.8	88.5	87.8
Color Reduction	82.4	85.1	89.9	89.2

Source: [23] [26]

V. EMERGING TRENDS AND FUTURE DIRECTIONS

A. *Explainable Ai (XAI) Integration*

Recent research promotes the integration of explain ability in forgery detection to facilitate legal admissibility and forensic transparency [20] [23]. Multi-modal large language models and vision transformers provide promising directions for interpretable detection.

B. *Attention Mechanisms And Transformer Architectures*

Transformer-based models with self-attention are investigated for enhanced context modeling and localizing at finer granularity [27] [16]. These models have the potential to outperform CNN-based models in modeling long-range dependencies.

C. *Hybrid And Multi-Modal Approaches*

Blending handcrafted forensic features with deep learning features [28] and fusing multi-modal sources of data (e.g., metadata, sensor data) promotes robustness and detection performance.

D. *Privacy-Preserving And Federated Learning*

Extending federated learning platforms to support various types of forgery and datasets responds to privacy and regulatory requirements and enables cooperative forensic intelligence [4].

E. *Expansion And Standardization Of Benchmarks*

Building exhaustive, high-fidelity datasets to mirror actual manipulations continues as a priority for standardizing evaluation and promoting generalizable models [1] [2].

VI. HOW OUR SURVEY DIFFERS FROM PRIOR SURVEY

Most earlier surveys on image forgery detection and localization have taken a broad view, covering many different deep learning models, traditional image processing methods, and a variety of forgery types such as splicing, copy–move, and deepfakes. While these overviews help in understanding the field as a whole, they usually mention ResNet and U-Net only briefly, grouping them with other models instead of exploring them in depth—either individually or as part of combined frameworks.

Our survey takes a different route. We focus specifically on ResNet, U-Net, and their hybrid versions, looking closely at how each architecture works and how they complement each other. By doing so, we are able to explain in detail how ResNet's residual connections help capture deep and complex features, and how U-Net's encoder–decoder design with skip connections achieves accurate, pixel-level segmentation. We also highlight how hybrid models bring together the strengths of both approaches, leading to better robustness, flexibility, and interpretability in real-world forensic applications.

A. Key Contributions of Our Survey

1) Architecture-Specific Benchmarking: We provide comparative results for ResNet-based, U-Net-based, and hybrid models using well-known datasets like CASIA2, MICC-F220, and MMTD-Set. This allows for a clear performance evaluation without the confusion that can arise from comparing different architectures.
2) Robustness-Focused Evaluation: Our survey examines how resilient each architecture is against common post-processing operations, such as JPEG compression, noise addition, and blurring. This aspect is often overlooked in earlier surveys, making our analysis particularly valuable.
3) Trend Mapping Within a Narrow Scope: We discuss emerging research directions, such as transformer-based augmentation, explainable AI integration, and privacy-preserving federated learning, specifically in relation to ResNet and U-Net frameworks. This focused discussion helps clarify how these trends apply to our chosen architectures rather than treating them as generic topics.
4) Forensic Applicability Linkage: We explicitly connect our methodological discussions to forensic requirements, addressing issues like cross-domain generalization, interpretability for legal purposes, and the integration of multimodal evidence sources. This ensures that our findings are relevant and applicable in forensic contexts.

VII. CONCLUSION AND FUTURE DIRECTIONS

This study highlights that ResNet and U-Net structures, separately and in hybrid versions, form the foundation of today's image forgery detection and localization technology. Their mutual strength—deep feature extraction and sharp segmentation—remedy central problems in detecting progressively advanced digital forgeries. Emerging trends like transformer incorporation, explainable AI, and privacy-protection federated learning are about to further advance the discipline.

Future work will need to emphasize generalizability to unobserved forgery methods, adversarial robustness, and interpretable model development appropriate for forensic and legal contexts. Enlargement and normalization of a variety of different benchmark datasets will be instrumental in furthering model evaluation and deployment preparedness.

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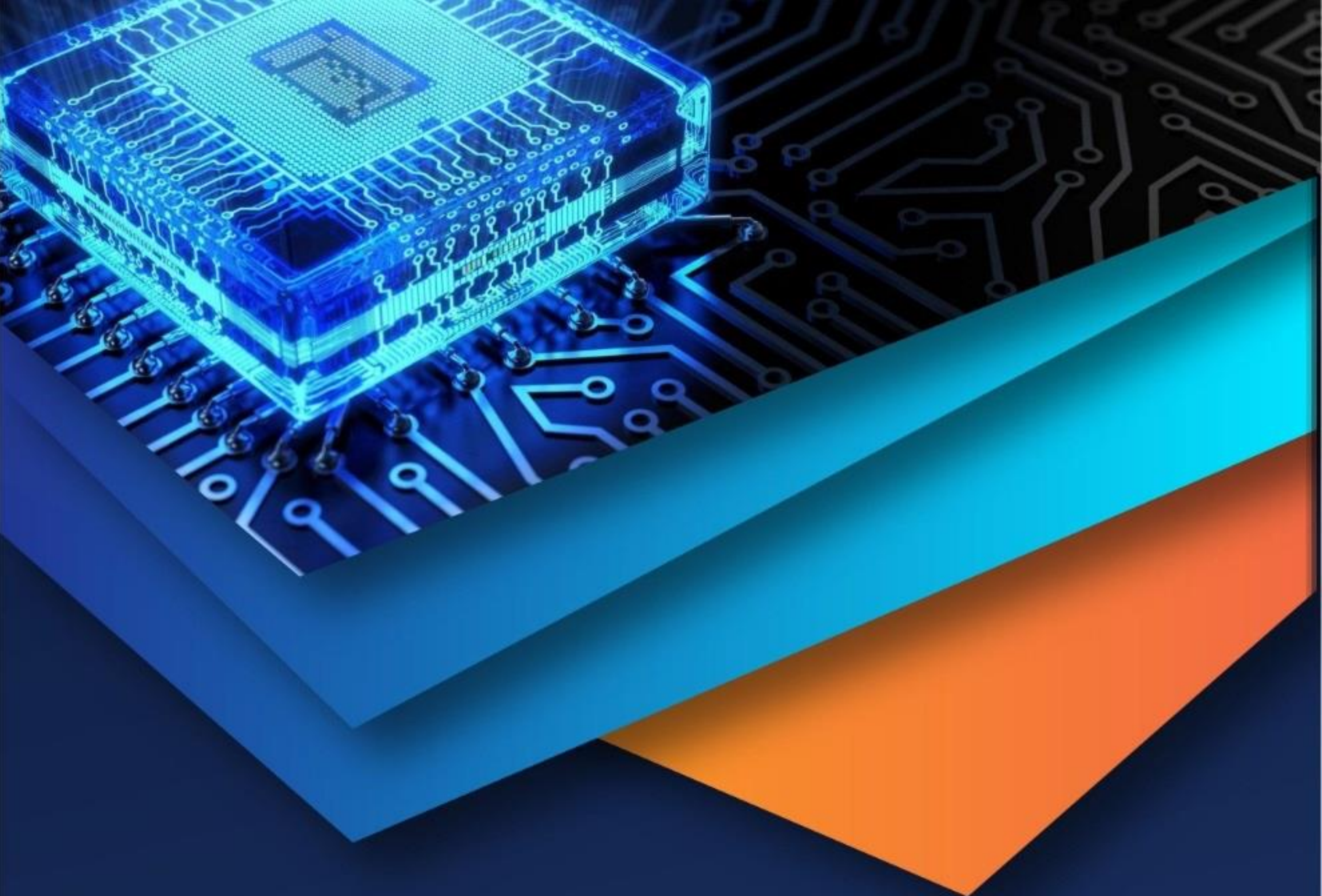

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