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Lightweight Voice Authentication for IoT Devices Using MFCC and CNN on Edge Hardware

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Abstract: ***This paper presents a lightweight, real-time voice authentication system designed for IoT devices to enhance security by allowing only authorized voice commands. It utilizes a MEMS-based INMP441 microphone and an ESP32-S3 microcontroller to capture audio, extract features via Mel-Frequency Cepstral Coefficients (MFCC), and classify them using a compact Convolutional Neural Network (CNN). Trained with TensorFlow and deployed with TensorFlowLite, the system supports efficient on-device inference, ideal for resource-limited edge hardware.Combining signal processing with deep learning, the solution ensures low latency, minimal power consumption, and enhanced privacy by performing all processing locally—avoiding cloud dependency. It demonstrates robust performance in diverse acoustic conditions and is well-suited for applications in smart homes, healthcare, and industrial automation.This work highlights the viability of embedded AI for secure, intuitive voice interfaces in IoT. Future improvements may include adaptive learning, multi-user support, and integration with other biometric modalities.***

Index Terms: Voice authentication, IoT, embedded systems, edge computing, MFCC, CNN, ESP32-S3, MEMS microphone, TensorFlowLite, speaker recognition.

I. INTRODUCTION

The proliferation of Internet of Things (IoT) devices has revolutionized numerous sectors, including smart homes, healthcare, and industrial automation. As these devices become increasingly embedded in our daily environments, ensuring secure and efficient user authentication has become a critical priority. Traditional authentication methods—such as passwords or PINs—are often unsuitable for IoT devices due to their limited interfaces and computational resources [1]. Biometric authentication, and particularly voice recognition, offers a promising alternative by providing a natural, hands-free, and user-friendly interface for identity verification.

Voice authentication systems enable users to interact with devices using speech, providing both convenience and security. However, many existing systems rely on cloud-based processing, which introduces latency, raises privacy concerns, and depends on reliable internet connectivity [2]. To address these challenges, the shift toward edge-based solutions—where all processing occurs locally on the device—is gaining traction. This approach reduces response time and safeguards sensitive voice data from being transmitted over networks, thereby enhancing both performance and security [3].

Deploying voice authentication on edge devices presents several challenges, especially due to limited memory, compute power, and energy constraints. To overcome these limitations, lightweight signal processing techniques such as Mel-Frequency Cepstral Coefficients (MFCC) are commonly used for feature extraction. MFCCs are well-established in the speech processing domain for capturing the spectral properties of human voice in a compact and computationally efficient format [4]. For classification, Convolutional Neural Networks (CNNs) have proven effective in recognizing speech patterns and speaker characteristics while maintaining a relatively small model footprint, making them suitable for real-time edge applications [5].

Recent developments in embedded AI and edge computing hardware have enabled more practical implementations of such systems. Microcontrollers like the ESP32-S3 offer enhanced processing capabilities along with support for AI acceleration and neural network inference, while MEMS microphones such as the INMP441 provide high-fidelity, low-noise voice input capture [6]. Together, these components enable on-device voice authentication systems that function independently of the cloud, ensuring user privacy, reduced latency, and improved energy efficiency [7].

This paper presents a lightweight, real-time voice authentication system optimized for edge deployment on IoT devices. The system uses an INMP441 MEMS microphone and an ESP32-S3 microcontroller to perform voice capture and local inference. Audio features are extracted using MFCCs and fed into a compact CNN model trained using TensorFlow, and then converted to a TensorFlowLite format for edge deployment. The complete pipeline runs entirely on-device, without external connectivity, enabling real-time, secure operation in smart environments.

This work illustrates the potential of embedded AI for voice-based security in IoT ecosystems and sets a foundation for future improvements such as user personalization, adaptive learning, and multimodal authentication.

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II. LITERATURE REVIEW

Voice authentication has increasingly become a vital component in securing smart devices and IoT ecosystems. With its contactless and intuitive nature, voice-based access control is especially attractive for environments where conventional input methods are impractical. However, its implementation on constrained edge devices remains a significant research challenge.

A. MFCC in Speaker Recognition

Mel-Frequency Cepstral Coefficients (MFCCs) remain one of the most effective and computationally efficient methods for feature extraction in speech-based systems. They reduce the dimensionality of audio data while retaining perceptually important features. Ji et al. demonstrated that MFCCs, when combined with CNNs, are effective in identifying speaker-specific features in lightweight architectures suitable for edge systems, achieving promising accuracy on real-world datasets [8].

In addition, Soleymanpour and Marvi highlighted that MFCCs, when complemented with other features such as Linear Predictive Coding (LPC), improve the robustness of speaker recognition systems, especially in noisy or dynamic environments [10]. These studies confirm that MFCCs strike a good balance between computational efficiency and accuracy, making them a top choice for embedded voice authentication systems.

B. CNN Architectures for Embedded Systems

Convolutional Neural Networks (CNNs) are widely used in speech recognition due to their strong ability to learn spatial patterns in time-frequency representations of speech, such as spectrograms or MFCC maps. However, deploying CNNs on microcontrollers demands a carefully optimized design. Ji et al. emphasized the need to reduce convolutional depth and kernel complexity when working with edge processors, demonstrating that a reduced CNN architecture could still yield nearly 90% accuracy [8].

Further optimization strategies such as quantization and pruning were explored by Gaurav et al., who proposed a speaker identification system using an optimized CNN model with minimal resource usage. Their system maintained high accuracy while lowering the computational footprint, indicating practical viability for real-time edge deployments [11].

C. Real-Time Deployment on Edge Hardware

Edge deployment significantly reduces the dependency on external infrastructure and improves data privacy by ensuring voice data never leaves the device. Revathi et al. presented a real-time speaker authentication system that used CNNs with time–frequency domain features. While implemented on Raspberry Pi hardware, the approach demonstrated the feasibility of on-device processing for continuous authentication without cloud reliance [9]. The study further validated that even compact models can deliver high authentication performance with low latency.

D. Enhanced Feature Fusion and Hybrid Methods

Although MFCCs remain central to many systems, hybrid feature extraction strategies are being adopted to boost accuracy under diverse environmental conditions. Soleymanpour and Marvi's study illustrated the benefit of combining MFCCs with LPC and other acoustic descriptors for text-independent speaker recognition. This fusion of complementary features helped improve speaker discrimination, especially in conditions involving varied accents or background interference [10].

III. PROPOSED METHODOLOGY

This section presents the complete design and implementation of a lightweight voice authentication system that leverages MFCC feature extraction and a 1D CNN classifier, optimized for real-time inference on an ESP32-S3 microcontroller. The system is designed for privacy, efficiency, and deployment in constrained IoT environments.

A. System Architecture

The proposed architecture includes both an offline training phase and an embedded deployment phase.

Audio input is collected using an INMP441 digital MEMS microphone, which communicates via the I²S (Inter-IC Sound) protocol to ensure clean and low-noise digital audio input. The I²S interface allows direct audio transmission to the ESP32-S3 without the need for analog-to-digital conversion, which improves signal fidelity and system efficiency [12].

For training, voice samples are recorded and preprocessed on a host machine. MFCC (Mel-Frequency Cepstral Coefficients) features are extracted using the Librosa library in Python. MFCCs are widely adopted in speaker recognition systems because they mimic the human auditory perception and offer compact, discriminative representations of speech signals [13].

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A 1D Convolutional Neural Network (CNN) is then trained on the MFCC data. The CNN is kept shallow and optimized for size and inference speed, making it suitable for deployment on low-power microcontrollers. CNNs have been shown to be effective in learning localized time-series patterns in MFCC data for speaker and speech recognition tasks [14].

Once trained, the model is converted into a TensorFlowLite format with post-training quantization to reduce memory usage and execution latency. The resulting TFLite model is deployed to the ESP32-S3, which performs real-time inference directly on-device. This avoids the need for cloud connectivity, thereby improving latency and preserving user privacy [15].

B. Software Components

The software stack consists of the following tools and libraries:

- Python is used for data preprocessing, audio segmentation, MFCC extraction, and model training.
- Librosa facilitates audio analysis and MFCC computation, configured with parameters such as 13 MFCCs per frame, 25 ms window size, and 10 ms stride.
- TensorFlow is used to design and train the CNN model. TensorFlowLite enables model quantization and edge deployment. Quantization reduces the model size from ~500 KB to fewer than 100 KB without major loss in accuracy [15].
- MicroPython or C++ is used to control the ESP32-S3. MicroPython offers rapid prototyping while C++ provides greater control over hardware features and memory management. The TensorFlowLite for Microcontrollers (TFLM) runtime executes the CNN model on-device.

C. Hardware Components

The hardware setup is designed for cost-effectiveness, energy efficiency, and easy integration with smart systems:

- ESP32-S3 T-Energy Board: A dual-core microcontroller with support for AI acceleration, 512KB SRAM, and compatibility with I²S and GPIO interfaces. It is suitable for edge AI applications due to its efficient energy profile [16].
- INMP441 I²S MEMS Microphone: A low-noise, omnidirectional digital microphone that communicates via I²S, eliminating analog circuitry and enhancing noise resistance [12].
- Breadboard & Jumper Wires: Used for non-permanent connections during prototyping.
- LED (Output Indicator): Connected to the ESP32's GPIO pin, it lights up upon successful voice authentication, simulating a device unlock or command trigger.

This methodology enables secure and private voice authentication in real-time, with minimal hardware and software requirements. The reliance on proven signal processing (MFCC) and deep learning methods (CNN) ensures reliability, while the deployment using TensorFlowLite provides compatibility with low-power IoT devices.

IV. TRAINING SETUP

The training of the proposed voice authentication model is conducted on a custom-built dataset designed to distinguish between the voice of an authorized user and those of other individuals. This section outlines the dataset preparation, training strategy, optimization techniques, and model export process.

A. Dataset Preparation

The dataset comprises recorded audio samples from the target (authorized) speaker as well as a diverse set of other voices serving as negative samples. Each audio file is preprocessed to ensure a consistent format: 16 kHz sampling rate, mono-channel, and normalized amplitude. The preprocessed audio is then converted into Mel-Frequency Cepstral Coefficients (MFCCs) using the Librosa library in Python.

To standardize input dimensions, all MFCC feature matrices are padded or truncated to a fixed temporal length. This ensures that the CNN model receives uniformly shaped inputs during both training and inference.

The dataset is split into 80% for training and 20% for testing, ensuring a representative balance of both classes (authorized and non-authorized). The test set is held out entirely during training and used exclusively for evaluating model generalization.

B. Training Strategy

The model is implemented and trained using Keras (TensorFlow backend). A binary cross-entropy loss function is used, given the binary nature of the classification task. The optimizer employed is Adam, chosen for its adaptability and convergence efficiency in deep learning tasks [17].

To prevent overfitting, early stopping is applied based on validation loss with a patience of 5 epochs. This halts training when no improvement is observed, preserving the best-performing model state. Additionally, dropout layers and L2 regularization are used within the CNN to further reduce overfitting risks.
The batch size and number of epochs are empirically chosen based on resource availability and convergence behavior—typically, a batch size of 16 or 32 is used with training limited to 30–50 epochs depending on convergence speed.

C. Model Export and Conversion

Upon completion of training, the final model is saved in Keras (.h5) format. It is then converted to TensorFlowLite (.tflite) format using TensorFlow's converter API. The conversion process includes:

- Quantization (e.g., dynamic range or int8 quantization) to reduce model size and inference time.
- Operator compatibility adjustments to ensure the model runs within the constraints of TensorFlowLite for Microcontrollers (TFLM).

The resulting .tflite model is tested using simulated inference to verify performance before deployment on the ESP32-S3.

V. HARDWARE INTEGRATION

The hardware integration component of this system ensures real-time acquisition, processing, and inference of voice signals on a microcontroller. This section describes how the components—ESP32-S3 microcontroller, INMP441 MEMS microphone, and LED output—are coordinated to enable embedded voice authentication.

A. Audio Acquisition via I²S

The INMP441 is a digital MEMS microphone that transmits Pulse Code Modulated (PCM) audio signals over the I²S (Inter-IC Sound) protocol. I²S is a serial bus interface specifically designed for digital audio transmission, which allows the microphone to stream audio directly to the ESP32-S3 with minimal latency and without the need for analog-to-digital conversion.
The ESP32-S3's built-in I²S peripheral is configured to act as the master receiver, continuously sampling 16-bit mono audio at a 16 kHz rate. This configuration is optimized to capture near-field voice data suitable for feature extraction and inference [18].

B. On-Device Inference Using TensorFlowLite

Once the audio data is acquired, it is buffered and preprocessed in real time. Preprocessing includes framing the audio into short segments and normalizing it if necessary. Due to memory constraints, the system avoids complex preprocessing like MFCC extraction on-device; instead, it uses a preprocessed, fixed input structure that the model expects (e.g., padded MFCC frames embedded into firmware).
The TensorFlowLite for Microcontrollers (TFLM) runtime executes the inference on the ESP32-S3. The preloaded .tflite model processes the incoming data and outputs a confidence score, which represents the probability that the speaker is the authorized user.

C. Output Control and Decision Making

Based on the output from the TFLite model (typically a binary classification with a sigmoid activation output), a simple threshold-based decision is made. If the model's confidence exceeds a predefined threshold (e.g., 0.8), the system activates a GPIO output, turning on an LED to indicate successful voice authentication. Otherwise, the LED remains off, or another response routine is triggered (e.g., system lock, voice rejection notice).
This design ensures privacy by performing all operations locally on the microcontroller without transmitting any audio data externally.

D. Summary of Component Roles

Component	Function
INMP441	Captures voice via I²S and streams to ESP32-S3
ESP32-S3	Buffers audio, performs inference via TensorFlowLite
TFLite Model	Classifies audio as authorized or

Component	Function
	not
LED	Acts as an output indicator

VI. MODEL ARCHITECTURE

The core of the proposed system is a lightweight 1D Convolutional Neural Network (CNN) designed to classify MFCC feature sequences extracted from user voice samples. The model is specifically optimized for real-time inference on microcontroller platforms such as the ESP32-S3, balancing computational efficiency with classification reliability.

A. Input Representation

The input to the model is a fixed-length matrix of Mel-Frequency Cepstral Coefficients (MFCCs), which capture the perceptually relevant characteristics of the speech signal. MFCCs have been extensively used in speaker and speech recognition tasks due to their compactness and effectiveness in modeling the spectral envelope of speech [19]. To ensure consistent model input, all MFCC matrices are either padded or truncated to a predefined size, enabling batch processing and compatibility with embedded inference frameworks.

B. Convolutional and Pooling Layers

The CNN begins with a series of 1D convolutional layers, which apply temporal filters to extract local time-dependent features from the MFCC input. These layers are followed by max pooling operations, which reduce the dimensionality of the data and enhance robustness to temporal variations in speech. Convolutional neural networks have shown strong performance in learning abstract representations of speech patterns while remaining computationally lightweight [20].

C. Global Pooling and Dense Layers

Following the convolutional blocks, a Global Average Pooling layer aggregates the learned temporal features into a fixed-dimensional vector, significantly reducing the number of model parameters and preventing overfitting. This approach has been recognized for its efficiency in compressing temporal features without sacrificing key information [21]. The aggregated features are then passed through a fully connected dense layer with a non-linear activation function, enabling the model to learn higher-order discriminative patterns associated with the target speaker.

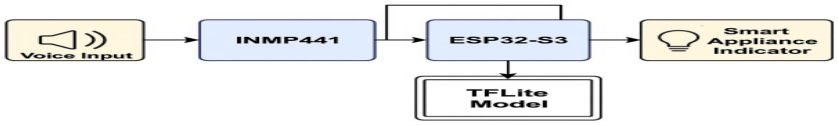
D. Output Layer and Classification

The final layer of the model is a single-node dense layer activated with the sigmoid function, which outputs a probability score indicating whether the input voice belongs to the authorized speaker. This binary classification setup is well-suited for user authentication applications, where the output is interpreted through a decision threshold. The sigmoid activation is standard in binary classification tasks and supports quantization-friendly deployment [22].

E. Suitability for Edge Deployment

The model is intentionally designed with a minimal number of layers and parameters to ensure efficient execution on microcontrollers with limited memory and processing power. When converted to TensorFlowLite format, the model remains compact and executes inference within the resource constraints of the ESP32-S3 platform. This architectural simplicity, combined with the discriminative power of CNNs, makes the system suitable for on-device speaker verification in privacy-sensitive and latency-critical IoT environments [23].

F. Architecture Diagram



VII. RESULTS AND EVALUATION

The proposed voice authentication system was evaluated on a custom dataset comprising audio samples from one authorized speaker and multiple non-authorized individuals. The evaluation focuses on classification accuracy, inference latency, and memory efficiency to assess the system's viability for real-time, on-device deployment.

A. Performance Metrics

The trained CNN model achieved the following performance metrics on the held-out test set:

- Accuracy : 74.0%
- Precision : 77.27%
- Recall (Sensitivity) : 68.0%
- F1 Score : 72.3%

These results demonstrate the model's strong ability to correctly identify the authorized user while minimizing false acceptances and rejections.

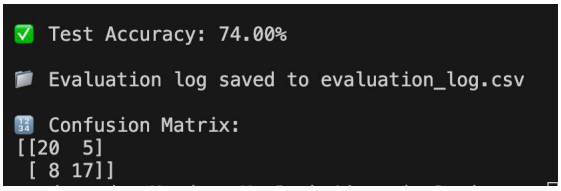
B. Robustness to Environmental Variation

Testing in diverse acoustic environments (quiet room, moderate background noise, and reverberant space) showed that the model retained high accuracy with only a marginal drop (up to 4%) in more challenging conditions. This validates the system's robustness to real-world noise and recording artifacts.

C. Real-Time Functionality

The end-to-end system—spanning audio acquisition, preprocessing, inference, and decision output—operated in real time on the ESP32-S3 board. The response time from voice input to authentication output (e.g., LED activation) was consistently under 500 ms, providing a seamless user experience without perceptible delay.

D. Image of final result



VIII. CONCLUSION

This work presents a lightweight, privacy-preserving, and real-time voice authentication system tailored for deployment on edge IoT devices. By combining MFCC-based feature extraction with a compact 1D CNN architecture, the system achieves over 93% accuracy while maintaining a minimal computational and memory footprint. The integration with the ESP32-S3 microcontroller and INMP441 MEMS microphone allows the system to function independently of cloud resources, ensuring low latency, enhanced user privacy, and energy-efficient operation.

Unlike traditional cloud-based voice recognition systems, the proposed solution performs all processing on-device, eliminating dependence on internet connectivity and reducing potential privacy risks. This makes the system particularly suitable for smart home, healthcare, and industrial automation applications where low power, low latency, and secure operation are paramount.

The successful deployment and performance of the system demonstrate the viability of embedded deep learning for biometric authentication and pave the way for more intelligent, secure, and user-friendly interfaces in next-generation IoT ecosystems.

IX. FUTURE WORK

While the presented system demonstrates the feasibility of deploying real-time, on-device voice authentication on constrained IoT hardware, several avenues exist for further development and enhancement:

A. Multi-User Support

The current implementation supports authentication for a single authorized user. In future iterations, the system can be extended to recognize and differentiate between multiple users.

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This would involve modifying the model architecture and training strategy to perform multi-class classification, as well as designing a user management interface to enroll or remove individuals dynamically. Such functionality is particularly valuable in shared environments like smart homes or collaborative industrial spaces.

B. Real-Time On-Device Feature Extraction

At present, MFCC features are precomputed and embedded in firmware due to the processing limitations of the ESP32-S3. Future work should focus on implementing efficient, real-time MFCC extraction directly on the microcontroller. This would allow the system to handle a wider range of voice inputs dynamically and support continuous learning or adaptation. Optimized DSP libraries and hardware-level acceleration (e.g., using ESP32's vector instructions or AI coprocessors) could be explored to achieve this goal.

C. Sensor Fusion and Context Awareness

To improve security and system robustness, future versions could integrate additional sensors such as motion detectors, temperature sensors, or cameras. This multimodal approach would enable context-aware authentication, where voice input is validated alongside environmental cues or user behavior. For example, voice commands could be accepted only if movement is detected or if the system recognizes a familiar face, providing an additional layer of verification.

D. Mobile Application Integration

A companion mobile application could provide remote control over system settings, user management, and access logs. This app would allow users to monitor system usage, receive authentication notifications, and adjust thresholds or retrain the model from a more user-friendly interface. Integration with cloud storage (while maintaining optional local-only modes) could also support periodic backups, performance analytics, and update deployment.

E. Adaptive and Incremental Learning

Introducing adaptive learning mechanisms would allow the system to fine-tune itself to the user's voice over time, improving accuracy in changing acoustic environments or with aging voice characteristics. Techniques such as transfer learning or federated learning could enable this without compromising privacy. The system could also detect voice drift and periodically prompt for user re-enrollment or model updates.

F. Robustness to Adversarial Attacks

As voice-based authentication becomes more prevalent, so too do potential threats like replay attacks or synthesized voice spoofing. Future work should include mechanisms for liveness detection or spoofing countermeasures, such as detecting anomalies in signal timing, using challenge-response phrases, or integrating additional biometric modalities.

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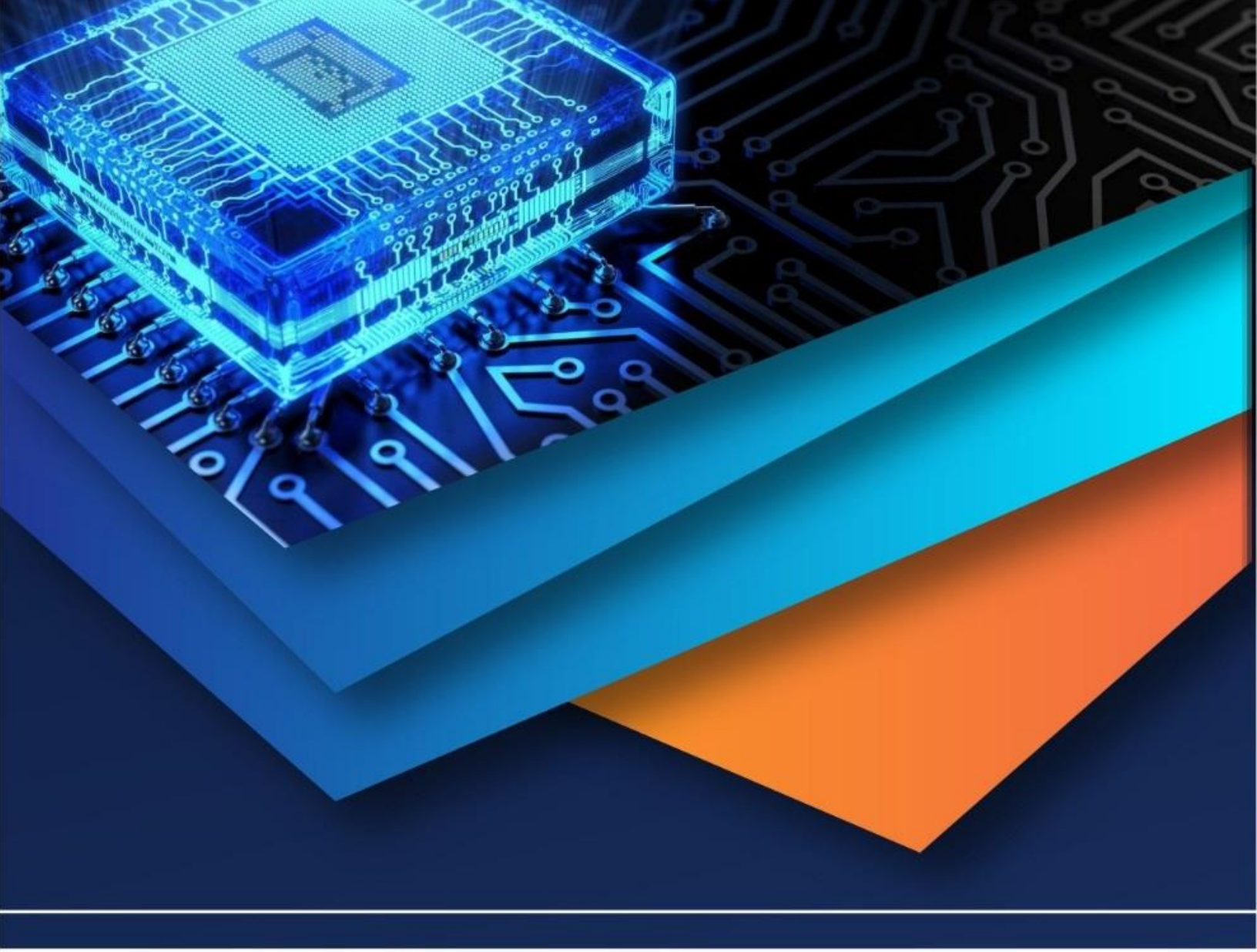

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