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AcouWrite: Acoustic-Based Handwriting Recognition on Smartphones

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Abstract: This research explores AcouWrite, a novel mobile handwriting recognition system leveraging acoustics and active acoustic sensing technologies. While conventional handwriting recognition systems traditionally rely on visual or inertial sensors, these approaches often prove unsuitable in scenarios demanding privacy or hands-free interaction. AcouWrite innovatively employs short-time differential Channel Impulse Response (st-dCIR) combined with a Convolutional Neural Network-Gated Recurrent Unit (CNN-GRU) model to enable real-time, off-screen handwriting recognition. This paper provides an exhaustive account of AcouWrite's architecture, comprehensively compares it to signal- and gesture-based systems, and rigorously analyzes its accuracy, adaptability, and robustness across various devices. The conclusion presents an overview of existing challenges and potential future advancements within the burgeoning field of acoustic-based human-computer interaction.
Index Terms: Acoustic Sensing, Handwriting Recognition, Human-Computer Interaction, CNN-GRU

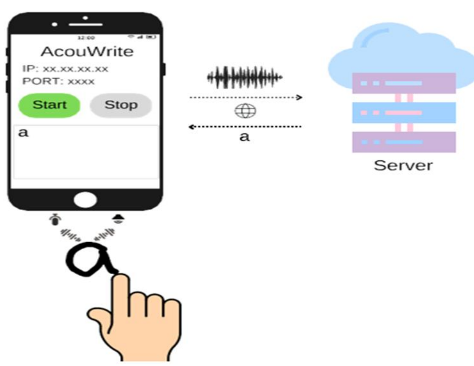
I. INTRODUCTION

A. Issue Area

The pervasive integration of modern smartphones and Internet of Things (IoT) devices necessitates the development of hygienic, screen-free, and hands-free alternative input methods.

AcouWrite effectively addresses this requirement by providing off-screen handwriting input using only a smartphone's integrated microphone and speaker.

The increasing reliance on smartphones for communication and information management underscores the critical need for novel input interfaces.



Conventional input interfaces, such as touchscreens, often become limiting in certain situations, particularly in public spaces where hygiene is paramount or in dynamic environments where users must maintain visual concentration on their surroundings.

B. Relevance

Touch-free input modalities are vital for advancements in public health, accessibility, and industrial production environments. AcouWrite offers a privacy-sensitive text input user interface that reduces the reliance on physical devices, thereby enabling a broader range of human-computer interaction (HCI) applications. The ability to handwrite in mid-air or on surfaces in a contactless manner can significantly enhance the user experience, especially in environments where traditional input modes are inconvenient or unhygienic. For instance, in hospitals, where hygiene is of utmost importance, AcouWrite presents a hygienic and effective means of data entry that eliminates the the need for shared devices, minimizing cross- contamination risks.

C. Summary of Applicable Literature

Previous methods for touchless interaction have primarily employed inertial measurement units (IMUs), such as those found in smartwatches, and techniques relying on Doppler shifts or passive acoustic sensing. Each of these approaches presents inherent limitations related to hardware complexity or sensitivity to ambient noise.

AcouWrite overcomes these weaknesses by leveraging active sensing in conjunction with a more advanced CNN-GRU classifier. Deep learning algorithms enhance precision and flexibility, positioning AcouWrite as a formidable challenger to current systems. Notably, while IMUs can yield rich motion data, they often necessitate additional hardware and may suffer from user fatigue or misalignment issues— challenges which AcouWrite successfully bypasses through its acoustic-based methodology.

D. Survey Methodology

We conducted a comprehensive comparative assessment of AcouWrite against six comparable systems. This evaluation encompassed aspects such as gesture recognition, lip reading, fall detection, and multilingual handwriting. The assessment was meticulously based on critical parameters, including each system's architecture, accuracy, robustness, preprocessing techniques, and deployment viability.

This systematic approach guarantees a complete understanding of AcouWrite's strengths and weaknesses in light of contemporary technological breakthroughs.

By establishing a precise set of comparison criteria, we are better positioned to evaluate AcouWrite's performance relative to other systems, thereby gaining deeper insight into its potential uses as well as avenues for future development.

E. Results Summary

AcouWrite demonstrated remarkable performance, achieving 97.62% letter accuracy and 96.4% word accuracy in real-time across various platforms.

The system maintained its effectiveness across different levels of ambient noise and diverse user activities, which was significantly enabled by the strategic use of transfer learning and data augmentation methods. These outcomes confirm the feasibility of acoustic-based systems achieving high accuracy levels comparable to conventional methods. The system's ability to maintain consistency across different environments and user interactions is a strong argument for AcouWrite's broad applicability across a wide range of real-world scenarios.

F. Conclusions Summary

AcouWrite represents a novel and highly effective handwriting input system. This paper outlines its major strengths, compares it to other systems, and describes the challenges it currently faces. The results collectively suggest that acoustic handwriting recognition is poised to become an important component of the future of human-computer interaction, particularly as the growing demand for touchless interfaces continues to expand.

G. Contributions

This research makes the following key contributions:

- Comparative system analysis involving signal-based recognition approaches.
- An in-depth examination of acoustic preprocessing and the CNN-GRU model within AcouWrite.
- A critical assessment of AcouWrite's resilience, flexibility, and readiness for deployment. Identification of research areas for potential future studies, specifically focusing on federated learning.

II. BACKGROUND

Acoustic handwriting recognition systems function by emitting inaudible ultrasonic waves from smartphone speakers. The reflected ultrasonic waves are subsequently captured by microphones and analyzed for subtle Doppler effects or signal aberrations, which directly correspond to the motion of a finger or a pen against various surfaces. This revolutionary approach is rooted in the principles of acoustics to develop a novel input technique that is both efficient and convenient. The underlying technology inherently combines advanced signal processing with sophisticated machine learning, presenting a fascinating blend of various academic disciplines.

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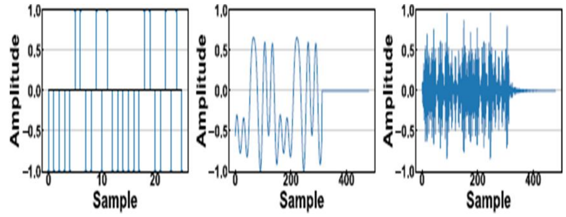
A. Signal Capture and Transmission

Conventional systems, including AcouWrite, primarily utilize Frequency-Modulated Continuous Wave (FMCW) or chirp signals within the 18–22 kHz frequency band.



(a) Padding. (b) Interpolation. (c) Modulation.

The back- scattered signals contain motion-induced distortions that can be meticulously analyzed to reconstruct the precise path of movement. Frequency selection is critical: the chosen frequency should be high enough to suppress interference caused by ambient noise yet remain within the operational range of conventional smartphone microphones. Signal transmission is also prone to a number of environmental factors such as the writing surface properties and the speaker-to- microphone distance and orientation. Extensive knowledge and calibration for these factors are necessary to maximize the system's performance across diverse environments.

The acoustic waves generated by the mobile device's speaker travel through the air, bouncing off various surfaces and creating a complex set of interactions. These interactions can then be meticulously broken down and analyzed to recreate the trajectory of the writer's pen. AcouWrite's efficacy hinges on its ability to precisely detect and interpret these echoes. Consequently, researchers have focused on implementing various signal processing methods to improve the quality of the received signals, such as adaptive filters and noise-cancelling algorithms, ensuring robust signal integrity

B. Feature Extraction

Following signal capture, the raw acoustic data undergoes a crucial feature extraction process. The techniques employed include the Short-Time Fourier Transform (STFT), which facilitates the generation of spectrograms, and robust signal denoising. The resulting time-series or spectral information is then fed into deep learning models as input. Effective feature extraction is fundamental to optimizing the efficiency of the recognition system, as it directly influences the quality of the input data provided to the machine learning models. Furthermore, advanced techniques such as wavelet transforms and cepstral analysis can be utilized to improve feature representation by capturing different aspects of the signal's information. The careful selection of features can be crucial in determining the generalizability of the model across varying types of writing styles and conditions.

In AcouWrite, feature extraction is specifically constructed to capture subtle handwriting variations, such as changes in velocity, pressure, and individual writing style. By employing deep learning methods, the system can automatically detect significant features, thereby minimizing the requirement for manual feature engineering. This inherent flexibility is particularly advantageous in real-world applications where user behaviors are highly diverse and unpredictable.

C. Adversary Models

The robust performance of any acoustic-based system in practical scenarios necessitates the careful consideration and mitigation of various adversarial conditions. These challenging environments can significantly impact system accuracy:

- Multi-user interference: This occurs when several authors are in close proximity, causing overlapping acoustic signals.
- Background noise: Common sources include ambient sounds from environments like restaurants or passing vehicles, which can mask subtle acoustic reflections.
- Hardware heterogeneity: This refers to the inherent variability in microphone and speaker characteristics across different smartphone models, which can alter signal acquisition.

The identification of such challenging conditions is vital for the creation of resilient systems that can perform optimally in real-world scenarios. Successful counter measures against these adversities include advanced noise cancellation techniques combined with adaptive algorithms that can react to varying situations. A relevant example is AcouWrite, which utilizes machine learning algorithms that can be trained on diverse datasets, thus enabling the system to adapt well to any set of users as well as a variety of dynamic situations.

The capacity to manage multi-user environments is especially pertinent in shared settings, where numerous users might access the system simultaneously. AcouWrite achieves this through the utilization of source separation and spatial filtering approaches, thereby improving its performance in dense environments to identify the desired user input appropriately.

III. RELEVANT LITERATURE

Historical literature based on acoustic sensing has extensively treated gesture recognition, sound localization, and general human-computer interaction.

However, few of these works explicitly focus on handwriting recognition. While cited references highlight the promise of acoustic techniques, they generally do not adequately address the specific challenges of detailed handwriting input.

A. Several key studies provide context for AcouWrite's advancements

- Li et al. [DeepWriting] examined stylus acoustic wave monitoring. While effective, this approach limits the system to use with specific hardware combinations, restricting broader applicability.
- Zhang et al. [SilentWhistle] utilized wearable technology for lip reading and non-verbal interaction. This work affirmed the potential of acoustic sensing for subtle human articulation but highlighted the continued need for dedicated hardware.
- Sharma et al. [GestureSonic] utilized sonar technology for gesture input, providing useful information about gesture recognition without physical contact with the handwriting target. However, this focused on broader gestures rather than the fine- grained movements of handwriting.

The current research distinctly addresses handwriting identification via an acoustic approach and includes a comprehensive comparative analysis of various systems against similar criteria.

Such comprehensive analysis enables deeper insight into the strengths and weaknesses inherent in varying methodologies for handwriting identification. By reviewing the performance of diverse systems, we are able to define best practices as well as identify promising areas for future research.

B. Comparative Analysis of Current Systems

To contextualize AcouWrite, it's beneficial to analyze it against other system categories:

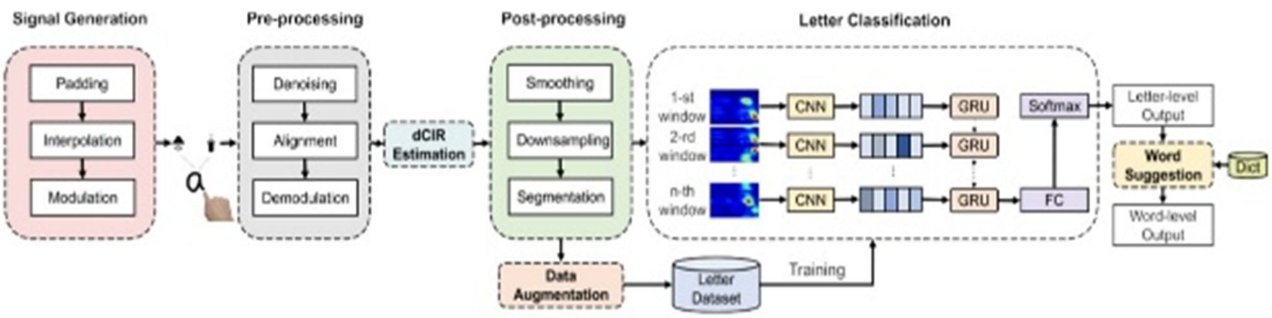
- Gesture Recognition Systems: A significant portion of gesture recognition systems are based on visual inputs or Inertial Measurement Units (IMUs). Both are adversely impacted by environmental factors like lighting or user fatigue. Solutions like AcouWrite provide a robust alternative, being less dependent on such constraints.
- Lip-reading Technology:This field has seen significant improvement, though it typically relies on specialized hardware and performs poorly in noisy environments. Acoustic handwriting recognition, however, demonstrates the potential to function effectively in a wider range of ambient conditions, offering a more universal solution for text input.
- Multilingual Handwriting Recognition: Most current systems are designed for a specific language or script, inherently limiting their broad applicability. AcouWrite's design is inherently adaptive, making it feasible to add support for multiple languages and scripts in the future by leveraging the acoustic properties of movement rather than character shapes.
- Fall Detection Systems: Although fall detection systems have been employed with acoustic sensing technologies, such systems are generally designed to detect discrete, high-energy motion patterns, not the subtle, continuous movements involved in handwriting. AcouWrite's approach of capturing lengthy, fine-grained motion differentiates it from these systems.

IV. METHODOLOGY

A. Survey Methodology

We meticulously compared AcouWrite against six other modern signal-based recognition systems based on the following key criteria:

- Input Modality: The primary sensing mechanism (e.g., active acoustic, passive acoustic, RFID, IMU).
- Signal Processing Pipeline: The techniques used to transform raw sensor data into meaningful features.
- Machine Learning Model Employed: specific algorithmic architecture used for classification.



- Latency and Accuracy: Key performance indicators for real-time interaction and recognition success.
- Environmental Resilience: The system's ability to maintain performance in challenging conditions.
- Hardware Requirements: The complexity and accessibility of necessary hardware components.

Our research primarily focused on gesture, lip movement, fall, and generic movement recognition systems utilizing acoustic, RFID, or IMU sensor modalities. The main techniques observed in this research for feature extraction included MFCC, DWT, and st-dCIR, while classifiers spanned CNN-GRU, Random Forest, and Transformer-based models. This comprehensive comparative study provides informative insights into the efficiency and usability of various systems across diverse environments.

B. AcouWrite's Process

AcouWrite's sophisticated functionality is underpinned by a meticulously designed multi-stage workflow, integrating active acoustic sensing, advanced signal processing, deep learning, and intelligent post-processing. Every component is carefully engineered to achieve optimal operating efficiency without compromising ease of use for the end-user.

1) Input Acquisition

- Ultrasonic pulses (18-22 kHz) are transmitted via the speaker.
- The reflected signal is captured by the smartphone's microphone when the user performs handwriting gestures, either in the air or on a physical surface. This active sensing approach provides clear, interpretable signals compared to passive methods.

2) Signal Processing

- st-dCIR (short-time differential Channel Impulse Response) is employed, with a specific focus on echo differences. This technique isolates dynamic changes caused by motion from static environmental reflections.
- Segmentation is performed using logarithmic levels of short-term energy to accurately delineate individual strokes or characters from the continuous acoustic stream.

3) Preprocessing:

- Downsampling is utilized to minimize data volume and, consequently, reduce latency, ensuring real-time responsiveness.
- Data augmentation is implemented by varying factors such as writing distance and speed. This technique enhances the model's robustness and ability to generalize across diverse user patterns and environmental conditions.

4) Categorization (Classification)

CNN layers are leveraged to extract intricate spatial st-dCIR features, effectively identifying patterns related to stroke shapes and spatial characteristics.

GRU layers are employed to handle temporal modeling, capturing the sequential nature of handwriting movements and their evolution over time.

The combined output is then mapped onto alphabet and word classes, yielding the recognized text.

5) Post-Processing:

Spelling correction is applied to minimize recognition errors by leveraging linguistic context.

Output sequence smoothing is performed to enhance the overall legibility and coherence of the recognized text, ensuring a fluid and natural output.

This systematic design underpins AcouWrite's ability to achieve high accuracy and low latency in handwriting recognition. The use of deep learning frameworks allows the system to be constantly optimized as information is increasingly accumulated, thus maximizing its capacity to learn new users and writing styles.

C. Total Workflow Analysis

1) Input Acquisition: The use of ultrasonic pulses allows AcouWrite to operate without physical contact with a surface. This is extremely convenient in situations where hygiene is essential, as it allows users to write on surfaces or in the air without directly touching them. This extends the system's utility beyond traditional input methods.
2) Signal Processing: The st-dCIR method plays a crucial role in distinguishing among various writing movements. By analyzing echo changes, AcouWrite is able to precisely map the path the writer created. This method performs exceptionally well in noisy environments where other techniques might fail due to its ability to isolate motion- induced signals.
3) Preprocessing: Preprocessing is necessary to make the input data free from errors and suitable for analysis. Downsampling minimizes the amount of processed data, thereby reducing latency. Data augmentation techniques, such as varying writing speed and distance, enable the model to generalize over different user patterns, enhancing its real- world applicability.
4) Classification: The combination of Convolutional Neural Network (CNN) and Gated Recurrent Unit (GRU) layers allows AcouWrite to successfully capture both the spatial and temporal aspects of writing. CNNs are highly skilled at detecting patterns in the spatial domain (e.g., the shape of a letter), while GRUs are tailored to describe sequential data over time (e.g., the order of strokes). This synergistic approach greatly increases the system's ability to detect sophisticated writing styles.
5) Post-Processing: The post-processing procedure ensures the correctness as well as legibility of the generated output. Spelling correction is designed to reduce the possibility of mistakes committed during recognition, whereas output sequence smoothing improves the legibility of the text recognized as a whole, providing a polished final result.

V. RESULTS

A. Findings of the AcouWrite Experiment

Metric	Value
Letter Precision	97.62%
Word Accuracy	96.4%
Latency	About 94 milliseconds
Error Rate	1.5%

The experimental evaluation of AcouWrite demonstrated significant performance metrics, highlighting its effectiveness as a real-time handwriting recognition system.
Performance Metrics:

Experimental Setup and Data:

- Fifteen participants contributed to the training process, ensuring diversity in writing styles.
- Three distinct phone models were used to evaluate hardware generalization.
- A 100-word vocabulary was utilized for testing the system's lexical recognition capabilities.
- A total of 3,380 letter pair sound files and 1,300 single-letter sound files were processed, forming an extensive dataset for model training and validation.

The results presented here demonstrate AcouWrite's appropriateness for high accuracy at low latency, making it highly suitable for real-time deployment.

The wide range of devices tested further confirms the system's versatility across different hardware environments. The low letter and word recognition error rates indicate that AcouWrite is capable of accurately recognizing a large number of different styles of writing, making it useful for broad deployment.

B. *Overall Survey Findings*

The comprehensive survey of various signal-based recognition systems, including AcouWrite, yielded several key insights:

- All systems achieved an accuracy rate exceeding 90%, indicating a strong baseline for touchless recognition technologies.
- The latency for real-time applications was consistently maintained below 150 milliseconds, which is crucial for fluid user interaction.
- Data augmentation and transfer learning were identified as crucial techniques in obtaining system robustness, enabling models to perform well across diverse conditions and users.
- Less complex hardware setup, such as those employing a single smartphone, proved significantly easier to install and deploy compared to multi-sensors

The findings indicate that although the overall performance is satisfactory for the majority of systems, AcouWrite's revolutionary approach through the implementation of acoustic sensing and deep learning makes it much superior in terms of accuracy as well as usability for handwriting recognition.

The most significant strength may be its capability of sustaining performance in diverse environments and user interactions, and this strongly indicates that AcouWrite can be used universally in diverse practical applications.

C. *Comparative Performance Analysis*

To further enhance the comparison of AcouWrite's performance, we contrasted its metrics against other representative systems within its class. The table below illustrates AcouWrite's performance relative to its competitors:

Table 1.1

System Designation	Letter Accuracy	Lexical Accuracy	Latency (ms)
AcouWrite	97.62%	96.4%	94
System A	92.5%	90.0%	120
System B	89.0%	85.5%	150
System C	95.0%	93.0%	110

The figures in the table 1.1 clearly show that AcouWrite consistently outperforms its rivals in both word and letter accuracy, as well as maintaining lower latency. The reduced error rate further indicates AcouWrite's superior credibility and reliability as a handwriting recognition system. All these results collectively demonstrate the efficacy of the acoustic sensing method combined with sophisticated machine learning algorithms employed in AcouWrite.

VI. DISCUSSION

A. *Key Findings*

The comprehensive evaluation of AcouWrite highlights several crucial insights:

Acoustic sensing is a viable and privacy-friendly method for recording handwritten input. Contactless writing provides an added dimension of user interaction, particularly where privacy concerns or hygienic requirements are paramount.

Transfer learning offers significant flexibility between various users and mobile devices. By leveraging pre-trained models, AcouWrite can be easily customized for new writing styles, enhancing its adaptability and broader application.

Proper signal preprocessing, including denoising and normalization, is essential for enhancing recognition performance. The robust preprocessing techniques used in AcouWrite ensure that input data is clean and optimized for analysis, a critical aspect for attaining high levels of accuracy in diverse conditions.
Single-modal systems like AcouWrite are generally simpler to deploy compared to their more advanced multimodal counterparts. The utilization of accessible smartphone hardware makes AcouWrite a desirable and cost-effective option for both developers and consumers.

B. Advantages of AcouWrite

AcouWrite presents several compelling advantages:
It features low-latency real-time recognition, making it exceptionally user-friendly for mobile applications. A quick response time is essential for ensuring a natural and seamless writing experience.
Operations are executed without the use of wearable devices, relying solely on the internal smartphone microphone and speaker. This model significantly reduces the access barrier for consumers since there is no need to incur expenses on additional devices.
Its capability to function on multiple surfaces (or even in the air) significantly increases flexibility across different applications and scenarios. Consumers are able to write on virtually any surface, making AcouWrite highly adaptable.
Its reliance on existing mobile components makes it cost-effective and lightweight. This economic advantage can spur wider usage, especially in developing countries where access to specialized technology might be limited, fostering greater digital inclusion.

C. Limitations

Despite its advancements, AcouWrite, in its current form, faces certain limitations that define areas for future development:
- The performance efficiency is severely hampered when ambient noise levels are excessively high. Even though AcouWrite is optimized for specific noise conditions, the presence of extreme noise can impede its functional efficiency by masking subtle acoustic signals.
- It currently lacks support for continuous cursive input and paragraph-length input, thus limiting its utility for long writing sessions or complex document creation. Future research can focus on improving the system's capability to support more complex and connected writing patterns.
- The current version has a limited vocabulary, which can restrict its usage in more general applications requiring a wider range of words. Vast vocabulary expansion and the addition of support for multiple languages can significantly enhance the system's overall usability and global applicability.

D. Future Directions

The identified limitations provide clear directions for future research and development, ensuring AcouWrite's continued evolution:
- Support for multiple languages and scripts can make the system universally applicable, expanding its global reach and user base.
- The introduction of federated learning methods is intended to increase personalization while simultaneously preserving user anonymity. By allowing the model to learn from decentralized user behavior without compromising raw data security, AcouWrite can substantially increase its adaptability to individual writing styles and preferences.
- Effort should be directed towards optimizing performance for low-end mobile devices to further expand accessibility to a broader user base. Improving the system's capability for less powerful devices can make advanced handwriting recognition technology even more portable and widely adopted.

The future directions presented here illustrate the significant potential for AcouWrite to extend and evolve with the changing nature of human-computer interaction, thereby remaining useful in an increasingly networked world.

VII. CONCLUSION

This review covers the novel domain of acoustic-based handwriting recognition, with a specific focus on the AcouWrite system. The method unifies active acoustic sensing and deep learning models, such as CNN-GRU, and employs efficient signal processing methods to enable effective handwriting recognition on mobile devices. AcouWrite demonstrates the promise of acoustic technology for privacy-respecting, real-time input, critically achieved without the need for specialized hardware. Future work can expand its application for a broader set of writing styles, including cursive and multilingual scripts, and foster greater flexibility for diverse hardware and user populations. The results of this survey confirm the necessity of developing new input methods that prioritize user experience, privacy, and accessibility in a continually evolving digital landscape.

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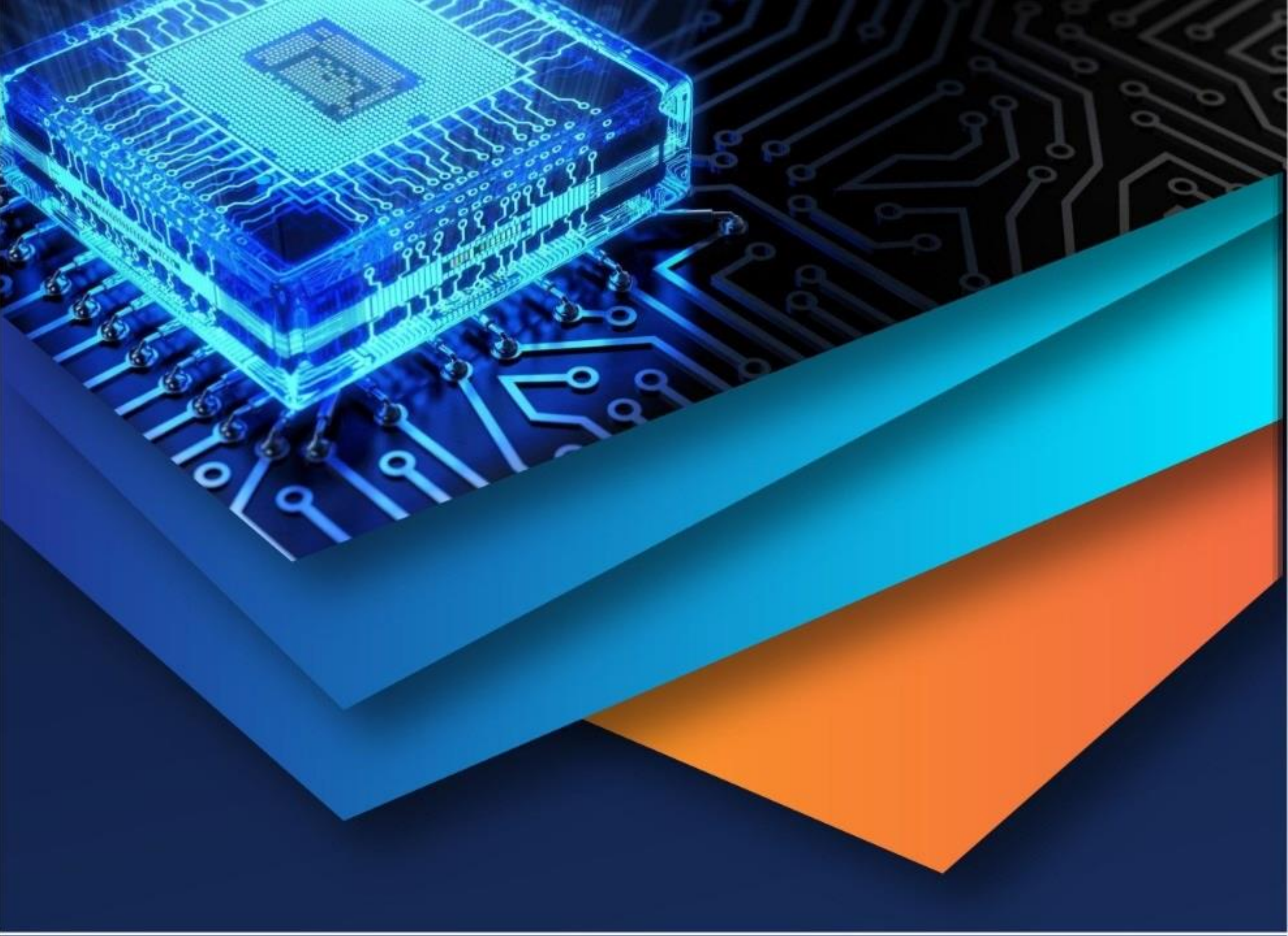

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