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Secure Path: An AI-Powered Companion for Real-Time Personal Safety

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Abstract: Personal safety is a growing concern, particularly for women and individuals traveling alone in urban environments. This paper presents SecurePath, an AI-powered voice-driven safety system designed to detect emotional states and trigger words in real time to enhance user security. The system integrates Speech Emotion Recognition (SER) and trigger-word detection using machine learning models based on MFCC feature extraction. A hybrid CNN–BiLSTM model with attention mechanism is employed for accurate emotion classification, while a CNN–LSTM model is used for efficient detection of emergency keywords.In addition to voice analysis, the system incorporates location-based unsafe zone detection to identify potentially risky environments. By combining emotional cues with contextual location data, SecurePath can automatically trigger alerts and notify trusted contacts when signs of distress or danger are detected. The models are implemented using TensorFlow and enhanced with data augmentation techniques to improve robustness and real-world performance.The proposed system demonstrates the effectiveness of AI-driven, context-aware safety solutions that operate without requiring manual intervention, offering a reliable approach to real-time personal security.
Keywords: Personal Safety, Speech Emotion Recognition, Trigger Word Detection, CNN, Bi-LSTM, LSTM, MFCC, Real-Time Alert System, AI-Powered Safety.

I. INTRODUCTION

Personal safety has become a significant concern in modern urban environments, with increasing incidents of harassment, theft, and unsafe travel conditions. Individuals—particularly women, students, and those traveling alone—often experience vulnerability in unfamiliar or poorly monitored locations. Existing mobile safety applications typically rely on manual activation, such as pressing an SOS button, which may not be feasible during high-stress or emergency situations.

To address these limitations, SecurePath is proposed as an AI-based real-time personal safety system that operates proactively without requiring user intervention. The system continuously monitors voice input and location data to detect signs of distress, unsafe zones, or deviations from predefined routes. It integrates Speech Emotion Recognition (SER) and trigger-word detection using deep learning techniques to identify emotional states and emergency cues from speech.

In addition, SecurePath incorporates contextual awareness by analyzing environmental factors such as crime-prone areas, lighting conditions, crowd density, and transportation accessibility. By combining voice-based emotion analysis with location-based risk assessment, the system is capable of generating timely alerts and notifying trusted contacts in potentially dangerous situations. This approach highlights the potential of intelligent, context-aware systems in enhancing real-time personal safety.

II. RELATED WORK

Deep learning–based speech processing has advanced significantly in recent years, enabling stronger performance in both Speech Emotion Recognition (SER) and Wake Word Detection. These two domains form the technological foundation for hands-free, real-time personal safety systems.

A. Literature Review

Research in Speech Emotion Recognition (SER) has evolved steadily over the years. Earlier systems mostly relied on basic acoustic features—like pitch and energy—combined with traditional machine-learning classifiers. These approaches worked for simple setups but struggled to capture the complexity of human emotions. As deep learning became more widely used, researchers began trying spectrogram-based CNN models. These models worked better because they could pick up emotional patterns directly from the audio rather than relying only on hand-crafted features [1].Some later works tried using both MFCC and Log-Mel features together, and this mix turned out to give CNN models more steady performance across different datasets and emotion groups [2].

A few studies also experimented with Probabilistic Neural Networks, which gave reasonably good results for classifying multiple emotions [3].

As SER research progressed, many works moved toward hybrid models such as CNN–LSTM and CNN–BiLSTM. These models handle both the spectral features and the time-changing nature of speech, which makes them more reliable when used on real speech data rather than controlled recordings [4][10].More recently, researchers have focused on making SER usable in real-world situations instead of only in lab conditions. Some studies link SER with wake-word detection so that systems can monitor audio continuously for safety applications [5]. SER has also been used in areas like assistive technology, robotics, and embedded devices to improve how systems interact with people [6]. At the same time, other work has looked at improving performance in noisy environments using raw-waveform processing and semi-supervised techniques [7][9].

Wake-word detection has followed a similar growth path. Lightweight CNN–LSTM and CNN–BiLSTM models now make it possible to run accurate keyword spotting even on mobile devices with limited resources [11]. Some systems also include speech-enhancement techniques to keep performance stable in noisy environments [12]. Some newer systems, such as HEiMDaL, focus on spotting keywords in long, uninterrupted audio streams [13].There are also multi-task systems that combine keyword spotting with speaker verification to make detection more personalized and secure [14]. Older methods like Dynamic Time Warping are still helpful in low-resource situations because they're simple and work reliably [16]. Recently, transformer-based models have shown good potential by reducing misdetections while still keeping up with real-time requirements [19]. Some studies have even explored multimodal approaches that combine audio with lip-movement tracking to improve accuracy in extremely noisy situations [18].

In parallel, many mobile safety apps have emerged. Most of them offer features such as GPS-based SOS alerts [20], AI-based threat detection [21], and geofencing or risk-prediction systems [22][23]. However, many of these apps still depend on manual triggers or a single input method, which makes them less helpful when the user can't respond quickly.

B. *Research Gap*

Most current speech-based safety systems dependon just one type of detection, either emotion recognition or keyword spotting. This becomes a significant limitation in real emergencies, where speech may be weak, unclear, or mixed with background noise. Many SER and wake-word models also show strong results in controlled environments but lose accuracy when used on mobile devices in everyday situations. Most safety apps still work only when the user presses an SOS button, and they don't analyze things like how safe the location is or any unusual changes in the user's behavior. These limitations leave a clear gap. There is a clear need for a system that combines emotion recognition, trigger-word detection, and location-based risk analysis, so it can respond on its own and help when the user isn't able to.

III. PROPOSED SYSTEM

This proposed SecurePath system integrates three main parts: distress detection from speech, trigger-word spotting, and location-based risk checking. For emotion detection, the system uses MFCC features with a CNN–BiLSTM–Attention model, and trigger words are identified using MFCC with a CNN–LSTM setup. Along with this, the app reads GPS and basic environmental details to find areas that may be unsafe and to recommend safer routes when needed.The outputs from all these components are combined so the system can send SOS alerts, share the user's live location, or guide them automatically during risky situations. The overall design is light enough to run smoothly on a mobile device with low delay, making it practical for everyday use.

A. *System Overview*

SecurePath is a safety system that keeps an eye on a user's voice and location to spot possible emergencies. It has three main parts: emotion detection, trigger-word detection, and checking if the area is safe. The system changes audio into MFCCs for the emotion part and the trigger-word part. These features are then passed to the deep learning models to check whether the user is upset or has spoken an emergency word.The system also keeps an eye on where the user is with GPS. It checks factors such as crime statistics, street lighting, crowd density, and transport availability. If the place doesn't feel safe, it can send an SOS, share the location, or give a little help. The user doesn't need to do anything—everything works on its own.

B. *System Architecture*

The architecture of SecurePath (Figure 1) is designed as a parallel, real-time safety system on a mobile device. It begins with the Location & Route Safety Module, which collects GPS data, plans routes, and identifies unsafe areas.

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This module utilizes two data sources for risk assessment: a pre-built offline dataset containing known high-risk locations and a real-time user-reported database that dynamically updates based on recent inputs.

A comparative risk scoring mechanism is applied, and the higher risk score from either source is considered for decision-making. In scenarios with limited or no network connectivity, the system seamlessly falls back to the offline dataset to ensure uninterrupted safety monitoring.

This information is managed by the Session & Monitoring Controller, which activates three subsystems simultaneously: the Speech Emotion Recognition (SER) model, which uses MFCC features with a CNN–BiLSTM–Attention architecture to detect emotional distress; the Trigger-Word Detection model, which uses MFCC features with CNN–LSTM layers to identify emergency keywords; and the Inactivity & Deviation Monitor, which tracks live GPS data, accelerometer inputs, and deviations from the planned route.

The outputs from these modules are integrated into the Decision Fusion Layer, which evaluates potential threats based on combined contextual inputs. If the system detects distress signals, emergency trigger words, or entry into unsafe zones, the Safety Response Module automatically initiates appropriate actions such as sending SOS alerts, sharing live location, recording audio, activating a fake shutdown mode, and notifying emergency contacts. Meanwhile, the Feedback & Heatmap Updating module continuously refines risk maps, improving the accuracy and adaptability of future safety predictions.

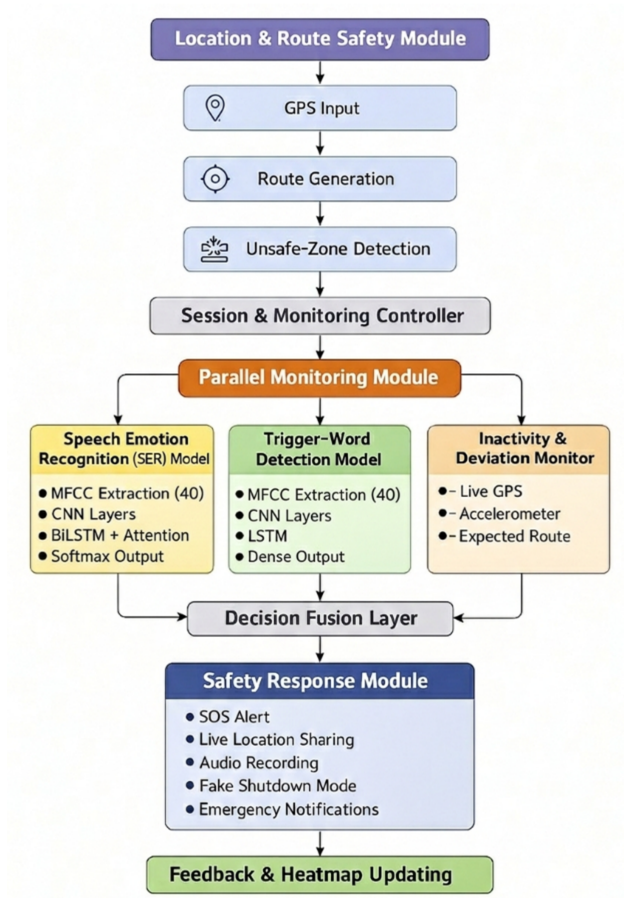

Fig 1. System Architecture

C. Block Diagram

The block diagram of SecurePath system has two main parts for processing audio. One part looks at the user's emotions in their speech (SER, Figure 2), and the other listens for emergency keywords (TWD, Figure 3). The audio is handled in two separate streams. The SER part uses MFCC features with a CNN–BiLSTM–Attention model to check if the user is upset, while the TWD part uses MFCC features with a CNN–LSTM model to detect any emergency words.The results from both modules go to a decision unit, which triggers safety actions whenever it detects that the user is upset or says an emergency word.

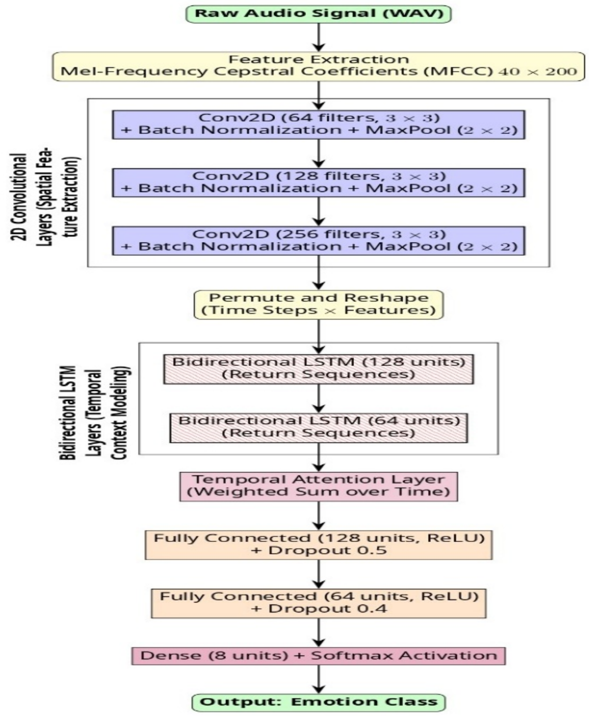

Fig 2. Block Diagram of the Speech Emotion Recognition Module

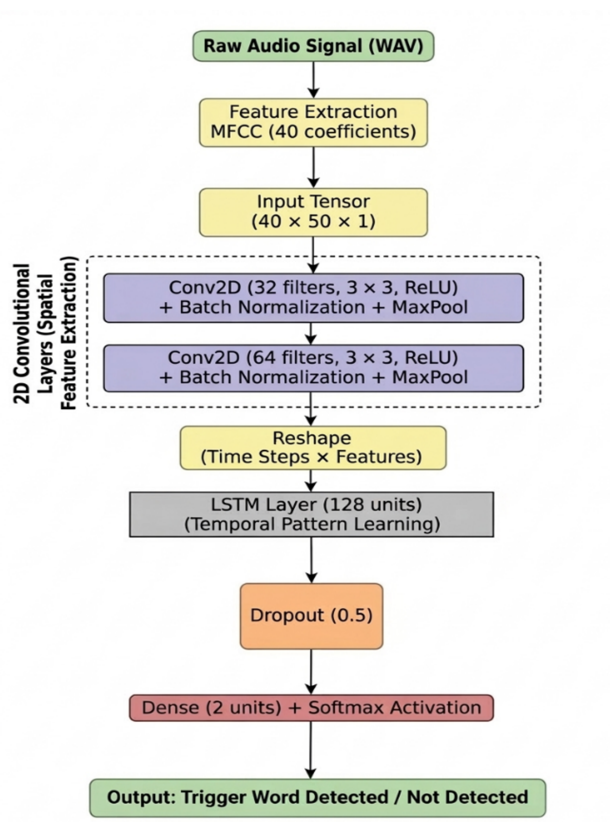

Fig 3. Block Diagram of the Trigger-Word Detection Module

D. Expected Output

SecurePath gives three main safety checks. The first, SER model listens to the user's voice and tells if they are scared, angry, upset, or calm. The second, TWDmodel listens for emergency words. The third, Unsafe-zone detection model checks the user's location with GPS and looks at things like crime, lighting, crowds, and transport to see if the area is safe. All three work together to watch the user and their surroundings all the time. If there's any danger or an unsafe spot, the system can automatically send an SOS, share the location, and record audio. This way, the user gets help fast without doing anything**.**

E. Model Architecture

SecurePath has two main models running at the same time: one to detect emotions in speech (SER) and another to spot emergency words (TWD). Both are made to run fast on mobile devices.

1) Speech Emotion Recognition (SER) Model:

The SER module uses a CNN–BiLSTM–Attention setup to figure out the user's emotions. It listens to small audios of the user's voice to detect the emotion.

a) The CNN layers pick up little cues in the voice that show emotions.

b) The BiLSTM layers follow the speech as it happens to spot quick changes in how the person is feeling.

c) The attention part helps the model pay extra attention to the most important bits of the voice.

This way, the model can tell if someone is scared, stressed, or angry, even in real life. On the RAVDESS dataset[24], it works about 94% of the time.

2) Trigger-Word Detection (TWD) Model:

The TWD module uses a CNN–LSTM model and is trained on a dataset of emergency words. It uses a kind of visual map of the sound, called MFCC, to understand the words.

a) CNN layers spot tiny patterns in the voice to see how the words are spoken.

b) The LSTM layers sees how the words come out over the period of time, so the system can catch emergency words even if the voice is unclear and noisy.

This model works well and catches emergency words most of the time with the accuracy of 96.4%.

3) Unsafe-Zone Monitoring Module

This module uses GPS data to evaluate area safety using both a pre-built offline dataset and real-time user-reported data. A comparative risk scoring mechanism selects the higher risk value to classify zones as safe or unsafe. In case of low or no network connectivity, the system relies on the offline dataset to ensure continuous monitoring.

F. Proposed Algorithm

SecurePath works step by step to keep the user safe, using voice and location together:

1) Audio Capture: The phone keeps listening to the user's voice all the time.

2) Feature Extraction: It uses MFCC features for the emotion detection model and emergency word detection model.

3) Emotion Classification (SER): The system detects the user's emotion like scared, stressed, or angry.

4) Trigger-Word Detection (TWD): It listens for any emergency words the user might say.

5) Location Monitoring: The system uses the user GPS to look at things like crime, lighting, crowd size, and transport. It also marks the zones as unsafe.

6) Automatic Safety Actions: If the system detects a potential threat, it automatically sends an SOS alert, shares the live location, and records audio.

7) Continuous Monitoring: The system repeats steps 1–6 until the user reaches the destination.

G. Dataset and Training

This system uses different datasets for its three main parts: Speech emotion detection, trigger words detection (TWD), and Unsafe-zone detection. For the SER part, it uses the RAVDESS dataset, which has recorded voices with eight different emotions. The audio is prepared by pulling out MFCC features, making sure all clips are the same length, and normalizing the data.

To help the model handle different voices and avoid overfitting, the audio is also slightly changed by stretching it, shifting the pitch, or adding a little noise. The TWD part is trained on a custom dataset of emergency trigger words recorded in different environments.It uses MFCC to represent the user audio.

The Unsafe-Zone Monitoring part doesn't use deep learning. Instead, it looks at the user's GPS and checks things like crime levels, lighting, how crowded the area is, and transport availability to figure out if a place is safe or risky. All the models are trained using an 80/20 split for training and testing, and tricks like learning rate scheduling, early stopping, batch normalization, and dropout are used to make the models stable and reliable.

IV. RESULTS AND DISCUSSION

The performance of the proposed SecurePath system was evaluated by analyzing its three main components: Speech Emotion Recognition (SER), Trigger Word Detection (TWD), and Unsafe-Zone Detection. Experiments were conducted using standard speech datasets and controlled test scenarios to assess classification accuracy and system reliability. This section presents a comparative analysis of different model architectures, followed by an evaluation of the final selected models for real-time personal safety applications.

A. Speech Emotion Recognition Results

Speech Emotion Recognition (SER) plays a critical role in identifying distress-related emotional states such as fear, anger, and stress from user speech. Multiple deep learning architectures were evaluated using MFCC features to determine the most effective model for real-time emotion detection. Table I summarizes the comparative performance of the evaluated SER architectures.

TABLE I. PERFORMANCE COMPARISON OF SER MODEL ARCHITECTURES

Model ID	Architecture Description	Accuracy (%)
M1	CNN + MFCC (baseline)	23.4
M2	CNN + BiLSTM	49.8
M3	CNN + BiLSTM + Attention	53.1
M4	CNN + BiLSTM + Corrected Attention + Dropout	72.0
M5	CNN + BiLSTM + Corrected Attention + BatchNorm	90.3
Proposed Model	3-CNN + 2-BiLSTM + Attention + Regularization	94.1

Table I presents the performance comparison of different CNN-based architectures evaluated for speech emotion recognition using MFCC features. A CNN-only baseline shows poor performance, indicating that spatial features alone are insufficient for emotion modeling. Introducing BiLSTM layers significantly improves accuracy by capturing temporal dependencies in speech signals. The addition of an attention mechanism further enhances performance by emphasizing emotionally salient segments. Regularization techniques such as dropout and batch normalization stabilize training and reduce overfitting. Based on this progressive evaluation, the final CNN–BiLSTM–Attention model achieves the highest accuracy of 94.1% and is selected as the proposed architecture.

B. Trigger Word Detection Results

Trigger Word Detection (TWD) enables the system to identify emergency keywords from continuous speech streams. Different CNN–LSTM configurations were evaluated to analyze the impact of architectural tuning and task formulation on detection performance. Table II presents the comparative results of the evaluated trigger word detection models.

TABLE II. PERFORMANCE COMPARISON OF TRIGGER WORD DETECTION MODELS

Model ID	Architecture	Accuracy (%)
T1	CNN + LSTM	47.1

T2	CNN + LSTM (tuned)	60.3
T3	CNN + LSTM (optimized)	86.7
Proposed Model	CNN + LSTM (binary classifier)	96.4

Table II presents the performance comparison of different Trigger Word Detection (TWD) models evaluated during system development. Initial CNN–LSTM models trained for multi-class keyword recognition showed moderate accuracy due to overlapping speech patterns and limited data. Progressive tuning of convolutional layers, regularization, and feature normalization improved performance to 86.7%. To further enhance robustness and reduce false activations, the task was reformulated as a binary classification problem distinguishing trigger and non-trigger speech. The final CNN–LSTM model achieved an accuracy of 96.4%, demonstrating reliable trigger word detection suitable for real-time personal safety applications.

C. Unsafe-Zone Detection Evaluation

In addition to speech-based monitoring, SecurePath incorporates a location-aware unsafe-zone detection module to assess environmental risk during user navigation. This module evaluates route safety using contextual parameters and supports proactive alert generation. Table III presents the quantitative evaluation of the unsafe-zone detection module.

The unsafe-zone detection module evaluates route safety using a weighted risk scoring mechanism that integrates multiple contextual parameters, including crime density, street lighting, crowd levels, public transport availability, and police presence. Each location is assigned an unsafe score computed using a linear weighted combination of these factors. Locations with unsafe scores exceeding a predefined threshold are classified as unsafe and trigger precautionary actions.

TABLE III.UNSAFE-ZONE DETECTION PERFORMANCE

Metric	Value
Zone classification accuracy	88.5%
False alert rate	9.2%
Average route evaluation time	1.4 s

The unsafe-zone module was evaluated using multiple real-world route scenarios extracted from the Virar location dataset. The system achieved a zone classification accuracy of 88.5%, indicating reliable differentiation between safe and unsafe areas. The false alert rate remained limited to 9.2%, ensuring that unnecessary alerts were minimized. Due to its lightweight, rule-based design, the average route risk evaluation and alert generation time was approximately 1.4 seconds. These results confirm that the unsafe-zone detection module can operate efficiently in real-time and effectively complement the speech-based safety models.

V. CONCLUSION AND FUTURE SCOPE

This paper presented SecurePath, an AI-powered personal safety system that integrates Speech Emotion Recognition (SER), Trigger Word Detection (TWD), and location-aware unsafe-zone detection for proactive safety assistance. Unlike conventional safety applications that rely on manual SOS activation, SecurePath continuously monitors user speech and environmental context to automatically identify distress situations.Experimental evaluation shows that the proposed SER model achieves 94.1% accuracy, while the optimized trigger word detection model reaches 96.4% accuracy using binary classification. The unsafe-zone detection module further supports the system by identifying risky locations with 88.5% accuracy and low response time. These results demonstrate that SecurePath can reliably detect unsafe situations and operate effectively for real-time personal safety applications.

Future enhancements include training the models on more diverse speech datasets to improve robustness across accents and noisy environments, integrating additional contextual inputs such as wearable or motion data, and refining location-based risk analysis using dynamic crime data. Further optimization will enable efficient deployment on resource-constrained mobile devices.

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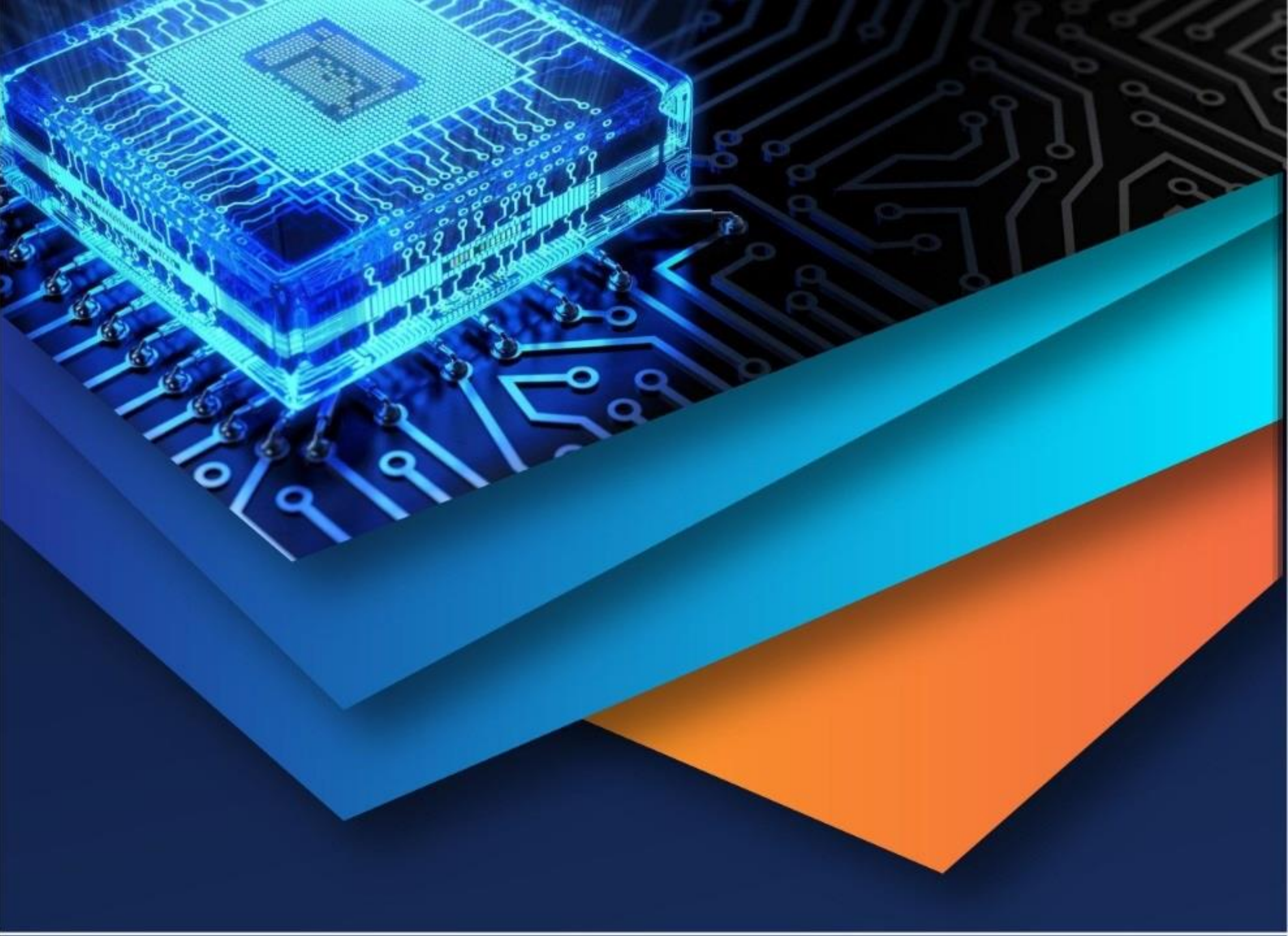

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