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NeuroSense: AI-Powered Multimodal Screening for Early-Stage Dementia

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***Abstract:** Dementia is a progressive neurological disorder that affects memory, cognition, behaviour, and daily functioning. Early detection is essential for effective intervention and improved patient outcomes. This paper proposes NeuroSense, an AI-powered multimodal system for early-stage dementia screening by integrating speech analysis, EEG signal processing, handwriting analysis, facial emotion recognition, and cognitive assessment. The system collects data from multiple modalities and processes it through preprocessing, feature extraction, and machine learning-based classification. Speech features such as MFCC, pitch, and pause duration, EEG frequency bands, handwriting patterns, and facial expressions are analysed independently and combined using a weighted decision fusion approach. The system is implemented using a React-based frontend and a Flask backend for real-time interaction and analysis. Experimental results show that the proposed model achieves an overall accuracy of 83%, with speech analysis contributing the highest performance among all modalities. The system provides a non-invasive, cost-effective, and interpretable solution for early dementia detection, supporting healthcare professionals in clinical decision-making.*
***Keywords:** Dementia Detection, Cognitive Assessment, EEG Analysis, Speech Analysis, Facial Recognition*

I. INTRODUCTION

Dementia is a progressive neurological disorder that primarily affects memory, cognitive abilities, behaviour, language, and daily functioning. It is a major cause of disability and dependency among older adults, significantly impacting the quality of life of patients and their families. According to global health statistics, millions of people worldwide are affected by dementia, and the number is expected to increase steadily due to aging populations. Early diagnosis is critical to manage symptoms, provide timely medical interventions, and plan long-term care. However, conventional methods of dementia detection rely on clinical assessments, cognitive tests, and imaging techniques, which are time-consuming, expensive, and often require specialized healthcare professionals. Recent advances in artificial intelligence (AI) and machine learning (ML) have opened new avenues for intelligent healthcare systems. By analysing behavioral, neurological, and physiological data, AI-based systems can provide accurate and early predictions of cognitive impairments. In this project, an intelligent dementia detection system is developed that integrates multiple analysis modules, including facial emotion recognition, speech analysis, EEG signal classification, behavioral assessment, and handwriting analysis. Facial emotion recognition and speech analysis help identify early changes in communication and emotional expression, while EEG and handwriting analysis detect neurological and motor impairments. The system is designed with a React-based frontend and a Flask backend API for seamless interaction between the user interface and machine learning models. Data collected from patients is processed using trained AI models to generate prediction results indicating the likelihood of dementia. The system aims to provide a non-invasive, efficient, and cost-effective preliminary screening tool, assisting healthcare professionals in the early detection of dementia and enabling timely medical intervention. By combining multiple indicators, the proposed system enhances diagnostic accuracy of 83% and reliability, demonstrating the potential of AI in modern healthcare applications.

II. LITERATURE SURVEY

A. Related works

1) Speech-Based Dementia Prediction Using Artificial Intelligence (2025)

This study presents a non-invasive approach for early dementia detection using speech analysis. Speech data from the Pitt Corpus was analysed by extracting acoustic features such as MFCC, chroma, pitch, jitter, and shimmer using tools like Librosa, Parselmouth, and OpenSMILE. Various classification models were applied, among which the Random Forest model achieved the highest accuracy of 93.48%. The study highlights that speech-based analysis is cost-effective and suitable for early screening; however, its performance is limited by small dataset size, sensitivity to noise, and lack of generalization across different languages.

2) Personalized Dementia Prediction Using Machine Learning Techniques (2025)
This work focuses on predicting dementia risk using personalized data including genetic, lifestyle, and health-related features. A dataset from Kaggle containing information on 1000 individuals was used, incorporating attributes such as age, cognitive scores, and medical history. Multiple classification models were implemented, with Random Forest achieving the highest accuracy of 98.75%. The approach demonstrates high prediction capability, but limitations include possible overfitting, dependency on structured data quality, and limited diversity in the dataset.

3) Multimodal Attention Network for Dementia Prediction (2024)
This paper introduces a multimodal attention-based framework that utilizes large-scale healthcare data from Taiwan's National Health Insurance database. The system integrates demographic and longitudinal medical records encoded using Word2Vec embeddings and processes them through multi-head attention mechanisms. The model achieved an AUC of 0.901, outperforming traditional methods. Despite its effectiveness, the approach requires complete medical history data and high computational resources, which may limit its practical implementation.

4) Predicting Dementia Screening and Staging Scores from Semantic Verbal Fluency Performance (2017)
This study investigates dementia detection using semantic verbal fluency tasks, where participants are asked to name items within a specific category. Linguistic and vocal features such as word count, pause duration, and semantic density were analysed using regression models. Support Vector Regression achieved the best performance in predicting clinical scores like MMSE. The method is simple and cost-effective but is constrained by moderate reliability, small dataset size, and dependence on language and transcription quality.

5) Early Detection of Dementia using Machine Learning for Predictive Analysis (2024)
This research proposes a hybrid approach combining multiple techniques for dementia detection using MRI data from the OASIS dataset. It includes demographic and neuroimaging features such as brain volume and cognitive scores. Various models were applied, with Ridge Classifier and CNN achieving the highest accuracy of 93%. While the approach provides high accuracy, it relies on expensive MRI data and involves high computational complexity, making it less suitable for large-scale screening.

6) Dementia Assessment Using Mandarin Speech with an Attention-Based Speech Recognition Encoder (2024)
This study presents a speech-based dementia assessment system designed for Mandarin-speaking individuals using an attention-based speech recognition model. The system uses a VGG encoder and Bi-LSTM layers to process speech data and predict clinical scores. It achieved an accuracy of 92.04% and demonstrated strong performance in dementia detection. However, the model is language-dependent and sensitive to variations in recording quality, which may affect its general applicability.

B. Research Gap
Existing studies on dementia detection primarily focus on single-modality approaches such as speech analysis, MRI data, or linguistic tasks, which limit the overall reliability and generalization of results. Although some multimodal systems have been proposed, they often rely on large-scale clinical datasets, expensive imaging techniques, or complex computational models that are not suitable for real-time or low-cost screening. Additionally, many approaches are constrained by factors such as small dataset size, language dependency, noise sensitivity, and lack of integration between behavioral, physiological, and cognitive indicators. There is also a lack of user-friendly and accessible systems that can provide quick and non-invasive preliminary screening. Therefore, there is a need for a cost-effective, integrated, and scalable multimodal system that combines diverse data sources and provides accurate, interpretable, and early-stage dementia detection suitable for practical healthcare applications.

III. PROPOSED SYSTEM
The proposed system, *NeuroSense*, is a multimodal framework designed for early-stage dementia screening by analysing physiological, behavioral, and cognitive indicators. The system follows a structured pipeline consisting of data acquisition, preprocessing, feature extraction, analysis, decision fusion, and result generation to ensure accurate and reliable detection.

A. Data Acquisition

In this stage, multimodal data is collected from various sources to capture different aspects of cognitive decline. Speech data is obtained from publicly available datasets , where participants describe a standard image, and also through real-time recordings using a microphone. EEG signals are collected from standard datasets or simulated data representing brain activity patterns. Handwriting samples are collected as images using a camera or touchscreen device, while facial expressions are captured through a webcam. Additionally, cognitive test responses are collected through structured questionnaires designed to evaluate memory, attention, and reasoning abilities.

B. Data Preprocessing

The collected raw data is processed to improve quality and remove noise and inconsistencies. EEG signals are filtered using bandpass filters and artifact removal techniques to eliminate unwanted interference. Speech signals undergo noise reduction, silence removal, and normalization to ensure consistency. Handwriting images are pre-processed through resizing, grayscale conversion, and binarization to enhance clarity. Facial images are processed using face detection and alignment techniques to extract relevant regions. Cognitive data is cleaned and normalized to maintain uniform scoring across users.

C. Feature Extraction

In this stage, meaningful features are extracted from each modality to represent patterns associated with cognitive decline. EEG data provides features such as power spectral density and frequency bands including delta, theta, alpha, and beta waves. Speech data yields features such as Mel-Frequency Cepstral Coefficients (MFCC), pitch, speech rate, jitter, shimmer, and pause duration. Handwriting analysis extracts features like stroke density, letter spacing, alignment, curvature, and texture patterns. Facial analysis captures facial landmarks, emotion probabilities, eye blink rate, and micro-expressions. Cognitive tests provide features such as accuracy, response time, and error rate.

D. Individual Modality Analysis

Each modality is analysed independently to evaluate its contribution to dementia detection. Speech analysis identifies hesitation, pauses, and vocal irregularities, while EEG analysis detects abnormal brain activity patterns. Handwriting analysis captures motor impairments and irregular writing patterns. Facial analysis evaluates emotional responses and expression changes, and cognitive tests assess functional performance. Each module generates a probability score ranging from 0 to 1, indicating the likelihood of dementia.

E. Decision Fusion

The outputs from all modalities are integrated using a weighted scoring mechanism to generate a final dementia risk score. Each modality contributes based on its reliability, with speech and cognitive analysis having higher weights compared to EEG and facial analysis. The final score is calculated using a weighted sum of individual modality scores, which improves overall accuracy and reduces false predictions by combining multiple indicators.

F. Risk Classification

The computed risk score is divided into three levels to simplify interpretation and support clinical decision-making. A score between 0 and 0.3 indicates normal cognitive function, suggesting no significant signs of impairment. Scores between 0.3 and 0.6 represent mild cognitive impairment (MCI), reflecting early-stage cognitive decline that may require monitoring and preventive intervention. A score between 0.6 and 1.0 indicates a high risk of dementia, associated with more severe cognitive deficits and the need for immediate medical evaluation. This classification helps convert numerical outputs into meaningful categories, allowing easier identification of cognitive status, early detection of potential decline, and timely intervention for better patient management.

IV. RESULT AND DISCUSSION

The final results are presented through a user-friendly web interface developed using frontend and backend technologies. The performance of the proposed NeuroSense system is evaluated using standard classification metrics. The model achieved an overall accuracy of 83%, with a precision of 81%, recall of 82%, and F1-score of 81%. These results demonstrate that the multimodal approach improves detection reliability and reduces misclassification compared to single-modality methods. A detailed PDF report is generated automatically, summarizing all results, analysis, and recommendations, which can be used by healthcare professionals for further evaluation and decision-making.

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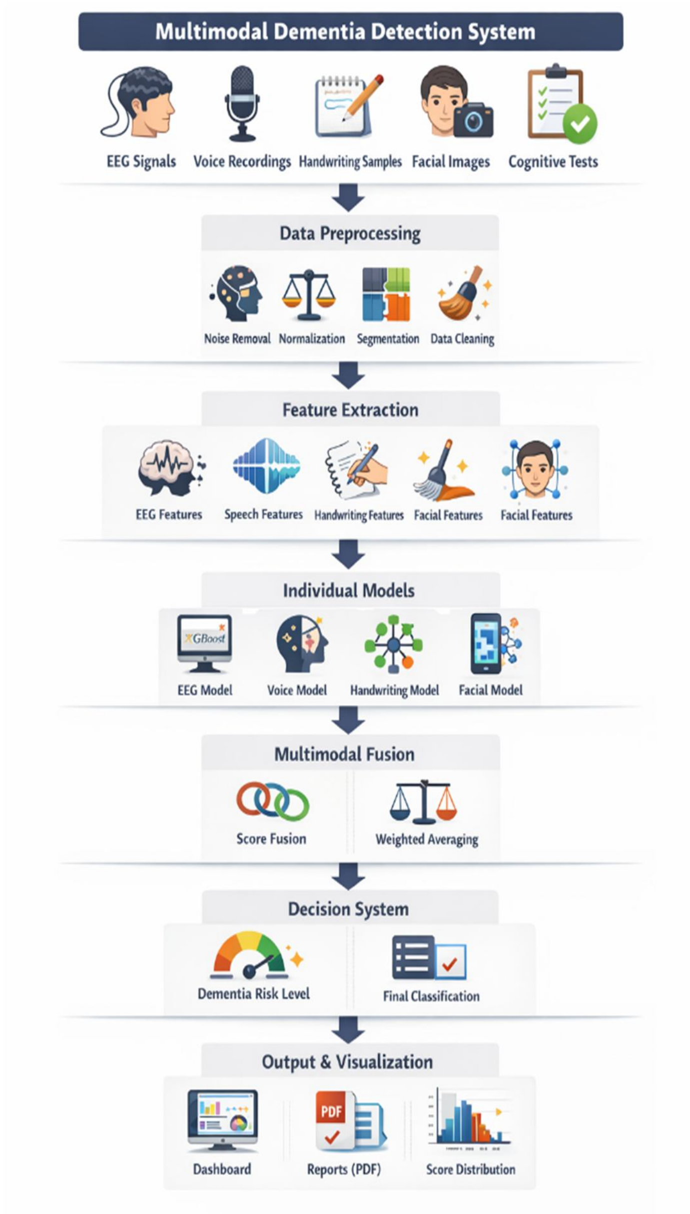

Fig 1: Architecture Diagram

A. Key Insights from Model Comparison

The comparison of the three model combinations shows clear differences in performance across speech, handwriting, EEG, and facial modalities.

- Model 1 (Random Forest + MobileNet + XGBoost + CNN) achieves the best overall performance, with the highest accuracy in speech (90%) and strong results in other modalities, indicating high reliability and low error rates.
- Model 2 (SVM + Random Forest + SVM + MobileNet) performs the weakest, especially in EEG (45%) and speech (55%), showing higher error rates and poor consistency.
- Model 3 (XGBoost + SVM + Random Forest + ResNet) provides moderate and stable performance across all modalities but does not exceed Model 1.

Overall, Model 1 is identified as the most effective approach, highlighting the advantage of combining ensemble and deep learning techniques for multimodal dementia detection.

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Table: 1 Weighted Contribution of Multimodal Features in Dementia Detection

Modality	Model	Accuracy	Weight (w_i)
Speech	RandomForest	90%	0.30
Handwriting	MobileNetV2 (image-based)	74%	0.20
EEG	XGBoost	65%	0.15
Facial	CNN (TensorFlow)	72%	0.15
Cognitive	Rule-based scoring	100%	0.20

B. *Analysis of Results*

The results show that model performance varies across different modalities. Speech data achieves the highest accuracy, making it the most reliable for dementia detection. Handwriting and facial analysis provide moderate performance, while EEG shows lower accuracy due to signal complexity. Among the tested models, Model 1 performs best with higher accuracy and lower error rates, indicating better stability and generalization. The findings confirm that combining multiple modalities improves overall detection performance compared to using a single data source

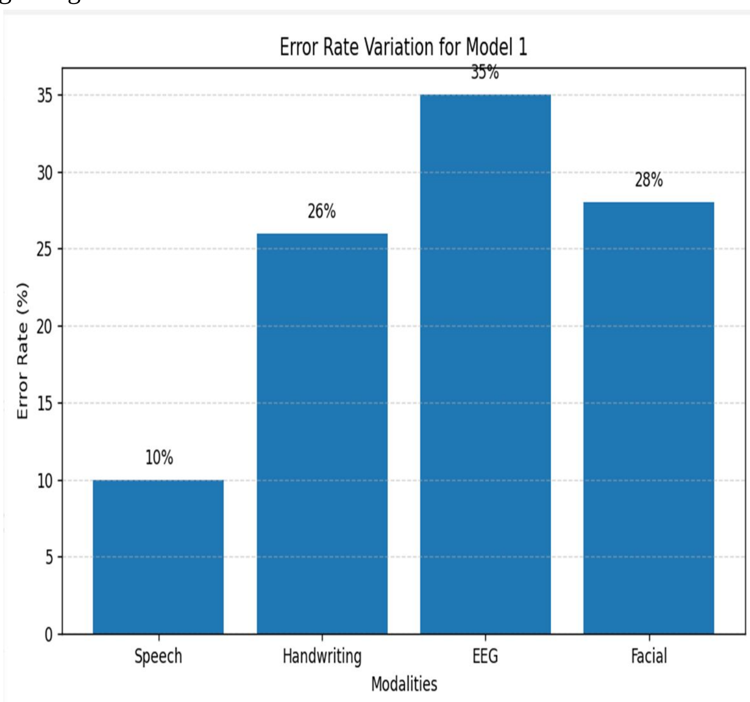

Fig 2: Error rate variation

C. *Novel Insights in Dementia Detection*

This study highlights that multimodal approaches greatly improve dementia detection accuracy by combining speech, handwriting, EEG, and facial data. Using machine learning and deep learning models enhances feature extraction and classification, capturing subtle patterns of cognitive decline. Among all modalities, speech is the most effective for early detection, reflecting early cognitive changes. Integrating multiple data sources provides a comprehensive and reliable assessment, reducing the limitations of single-modality approaches. This combination also improves prediction consistency and system robustness. Overall, the approach is suitable for real-world healthcare applications, supporting

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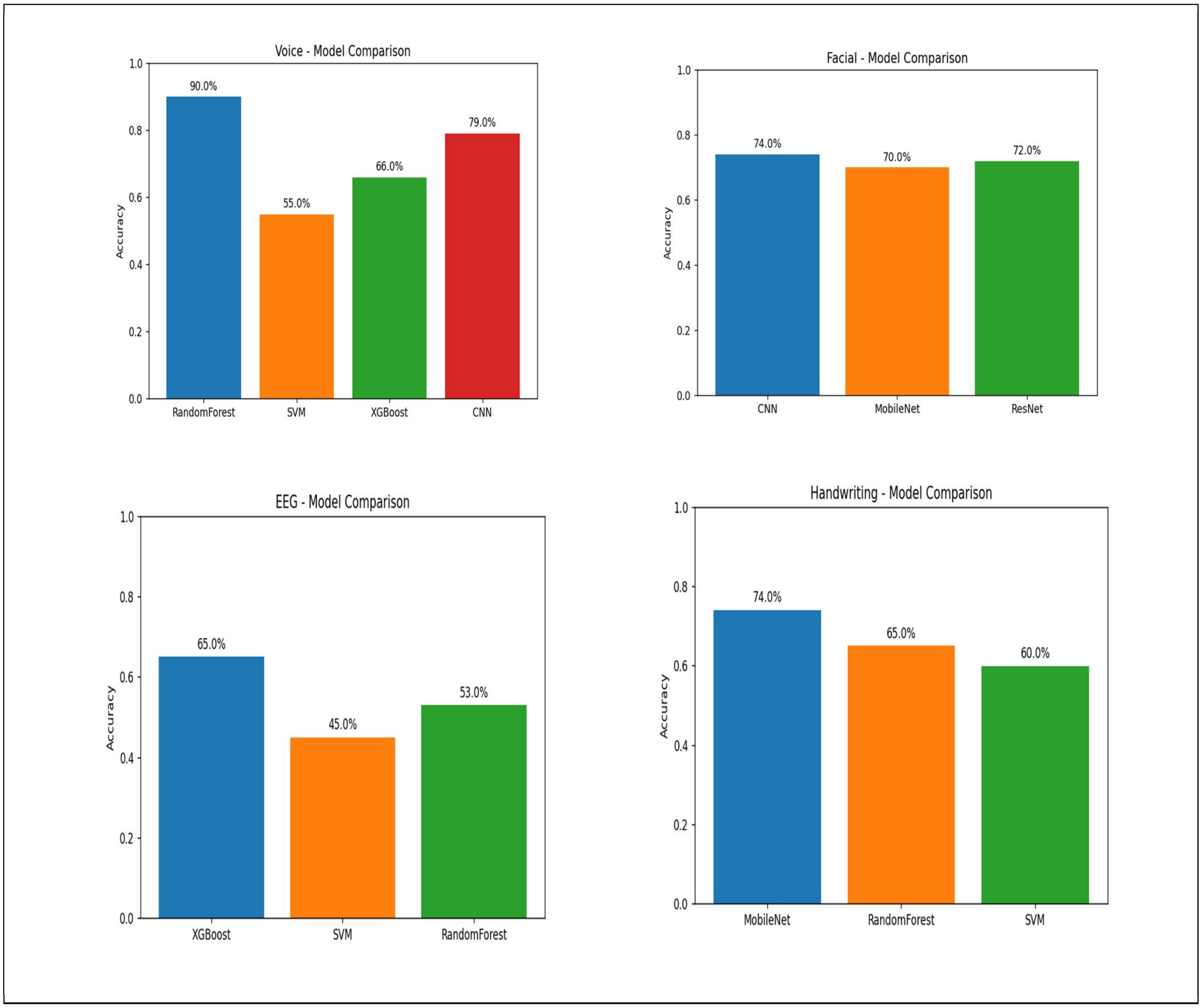

Fig 3: Overall comparison of my model

early diagnosis, continuous monitoring, and better clinical decision-making.

V. CONCLUSION AND FUTURE WORK

The NeuroSense multimodal dementia detection system demonstrates that integrating EEG, speech, handwriting, facial expressions, and cognitive assessments significantly enhances early-stage dementia screening compared to single-modality approaches. The use of XGBoost, MobileNet, CNN, along with a rule-based automated PDF reporting system, improves classification accuracy and supports practical clinical and remote monitoring applications.

For future work, the system can be further enhanced by incorporating additional modalities such as eye- tracking and gait analysis, which may capture subtle cognitive and motor changes. Advanced deep learning techniques, including transformers, can be applied to improve feature extraction and predictive performance. Developing real-time wearable or mobile monitoring systems would enable continuous assessment, while personalized risk models could provide individualized insights. Finally, conducting large-scale clinical trials will help validate scalability, robustness, and real-world applicability, ensuring the system can support early detection and long-term cognitive health monitoring effectively.

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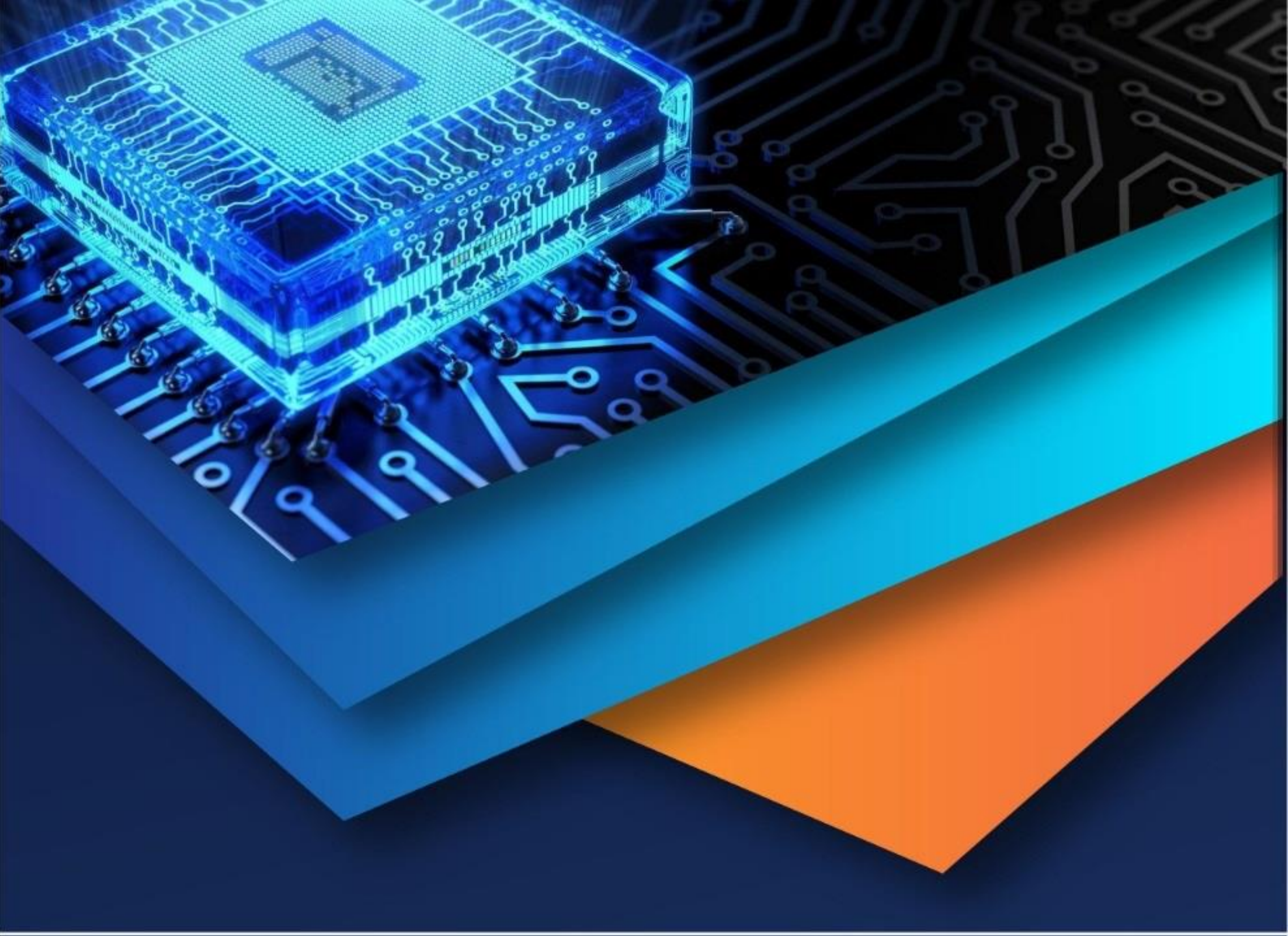

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