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Classical Quantum Federated Learning for Mental Stress Detection

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Abstract: The growing prevalence of mental stress has created a strong need for intelligent systems capable of early and accurate detection. This work proposes a hybrid learning framework that combines classical machine learning, quantum computing techniques, and federated learning to classify stress levels in in-dividuals. Initially, physiological signals from the WESAD dataset are processed to remove noise and normalize feature values. A Random Forest model is then applied to identify the most influential features, which helps reduce data dimensionality and makes the model suitable for quantum processing. The selected features are transformed into quantum states using rotation-based angle encoding with RY gates. A variational quantum neural network is designed to learn patterns within the encoded data through parameterized quantum circuits. To ensure data privacy and enable decentralized training, a federated learning strategy is incorporated, where multiple clients train models locally and share only model parameters. These parameters are combined using a federated averaging method to form a global model without exposing sensitive data. The developed system categorizes mental stress into three levels: low, medium, and high. The results indicate that integrating quantum learning with federated approaches can effectively handle sensitive health data while maintaining reliable classification performance. This study demonstrates the potential of combining emerging computational paradigms to build secure and efficient healthcare prediction systems.

Index Terms: Mental stress detection, quantum machine learning, variational quantum neural network, federated learn-ing, hybrid classical–quantum model, feature selection, random forest, RY rotation encoding, WESAD dataset, privacy-preserving learning, healthcare analytics.

I. INTRODUCTION

Mental stress has emerged as a significant public health concern due to rapid lifestyle changes, academic pressure, and increasing work-related demands. Persistent stress can lead to severe psychological and physiological disorders, making early detection and monitoring essential. Traditional methods for stress assessment often rely on self-reporting or clinical evaluations, which may be subjective, time-consuming, and not suitable for continuous monitoring. With the advancement of wearable sensors and data-driven technologies, there is a growing opportunity to develop intelligent systems that can automatically analyze physiological signals and provide accurate stress classification.

Machine learning techniques have been widely applied to stress detection using physiological datasets such as WESAD. These approaches are capable of identifying complex patterns in data and achieving reliable classification performance. How-ever, classical models often face challenges when dealing with high-dimensional data and may require significant computa-tional resources for optimization. In recent years, quantum machine learning has emerged as a promising paradigm that leverages principles of quantum mechanics to enhance com-putational efficiency and representational power. Variational quantum circuits, in particular, provide a flexible framework for building quantum neural networks capable of learning from encoded classical data. Another critical challenge in healthcare applications is maintaining data privacy and security. Physio-logical and mental health data are highly sensitive, and cen-tralized data collection raises concerns regarding unauthorized access and misuse. Federated learning addresses this issue by enabling decentralized model training, where data remains on local devices and only model parameters are shared with a central server. This approach not only enhances privacy but also allows collaborative learning across multiple data sources. In this work, a hybrid framework is proposed that inte-grates classical machine learning, quantum neural networks, and federated learning for mental stress detection. Initially, a Random Forest model is utilized to select the most relevant features from preprocessed physiological data, thereby re-ducing dimensionality and improving efficiency. The selected features are then encoded into quantum states using rotation-based encoding techniques, and a variational quantum neural network is trained to classify stress levels. To ensure privacy-preserving learning, a federated learning strategy is incorpo-rated, where multiple client models are trained locally and aggregated using a federated averaging method. The proposed system aims to classify mental stress into three categories: low, medium, and high stress.

By combining the strengths of classical and quantum approaches with decentralized learning, the framework provides an efficient and secure solution for stress detection. This study contributes to the development of next-generation intelligent healthcare systems that can operate with improved performance while safeguarding sensitive user data.

II. LITERATURE SURVEY

Recent research in mental healthcare has increasingly fo-cused on integrating advanced machine learning techniques with privacy-preserving mechanisms. Gupta et al. (2024) in-troduced a hybrid federated learning framework that combines clustering with quantum-based approaches to improve stress detection performance. Their model demonstrates enhanced scalability and privacy while achieving approximately 84 accuracy. The use of clustered federated learning (CFL) helps address data heterogeneity across clients, while quantum tech-niques improve feature representation. However, the tradeoff between computational complexity and system efficiency re-mains a challenge. In a related direction, Ullah et al. (2024) proposed a quantum-enhanced federated learning framework integrated with differential privacy mechanisms. Their ap-proach utilizes quantum encoding and encryption techniques to ensure secure data transmission and model training. Al-though the framework highlights the potential of combining quantum computing with federated learning, it largely relies on simulated quantum environments, which limits its real-world applicability. Additionally, the absence of practical quantum hardware integration restricts the demonstration of full system capabilities.

Further advancements have been made in privacy-focused stress detection models using explainable artificial intelligence. Meena et al. (2025) developed a federated learning-based system utilizing the WESAD dataset, achieving high clas-sification accuracy of approximately 92.56 . Their approach incorporates SMOTE for data balancing and LIME for model interpretability, enhancing both performance and transparency. Despite these improvements, challenges such as data hetero-geneity across clients and limited real-world validation remain unresolved. From a broader federated learning perspective, Lowy et al. (2023) explored privacy-preserving optimization techniques for non-convex federated learning without relying on a trusted central server. Their methods improve privacy and efficiency through differential privacy mechanisms, but practical implementation is complicated by issues such as hyperparameter tuning and increased privacy loss due to pre-processing steps. In the context of quantum federated systems, Ren et al. (2025) proposed a general architecture for quantum federated learning that integrates quantum circuits with dis-tributed optimization. While this work establishes a theoretical foundation for combining quantum and federated paradigms, it faces limitations in scalability due to restricted dataset usage and increased system complexity arising from hybrid integra-tion. Clustered federated learning has also been applied to healthcare monitoring scenarios. Jiang et al. (2024) presented a multi-domain learning framework based on ClusterGAN and graph neural networks to improve clustering efficiency in federated settings. Although this approach enhances learning across heterogeneous data sources, it relies heavily on accurate clustering and introduces additional computational overhead.

In practical healthcare applications, Alhamadi et al. (2023) implemented federated learning on Internet of Medical Things (IoMT) devices for stress detection using electrodermal ac-tivity signals. Their system ensures secure aggregation of local models; however, the added computational burden on resourceconstrained devices and vulnerability to adversarial attacks pose significant concerns. Earlier studies, such as the work by Reiss and Stricker (2022), have demonstrated the use of federated learning on wearable sensor datasets, including WESAD. These approaches effectively process multimodal physiological data such as ECG, EMG, EDA, and respiration signals. Nevertheless, they remain limited to classical machine learning techniques and do not incorporate quantum-based en-hancements. Overall, existing literature highlights significant progress in stress detection, quantum machine learning, and federated learning independently. However, there is a clear gap in developing a unified framework that effectively combines feature-efficient classical models, quantum neural networks, and privacy-preserving federated learning. The present work aims to address this gap by integrating these paradigms into a single system for accurate, scalable, and secure mental stress detection.

III. METHODOLOGY

The proposed methodology presents a hybrid framework that integrates classical machine learning, quantum neural networks, and federated learning for mental stress detection. The overall workflow consists of data preprocessing, feature selection, quantum data encoding, quantum model training, and federated aggregation. Initially, physiological data is ob-tained from the WESAD dataset, which includes signals such as electrodermal activity, heart rate, and respiration. The raw data is preprocessed to remove noise and inconsistencies, followed by normalization to ensure uniform feature scaling. This step improves the stability and convergence of subsequent learning models. To reduce data dimensionality and improve computational efficiency, a classical Random Forest classifier is employed for feature selection.

The model evaluates feature importance scores and selects the most relevant features contributing to stress classification. This step is particularly important for quantum models, as the number of input features directly affects the number of qubits required. The selected features are then transformed into quan-tum states using rotation-based angle encoding. Specifically, each feature value is mapped to a quantum rotation using RY gates, enabling the representation of classical data in a quantum Hilbert space. This encoding approach preserves the structure of the data while making it suitable for quantum processing. Following data encoding, a variational quantum neural network is constructed using parameterized quantum circuits. The circuit consists of rotation gates and entanglement layers that enable interaction between qubits. Trainable pa-rameters are optimized using classical optimization techniques to minimize a predefined loss function. The model learns to classify input data into three stress levels: low, medium, and high.

To ensure data privacy and enable decentralized learning, a federated learning strategy is incorporated. The dataset is

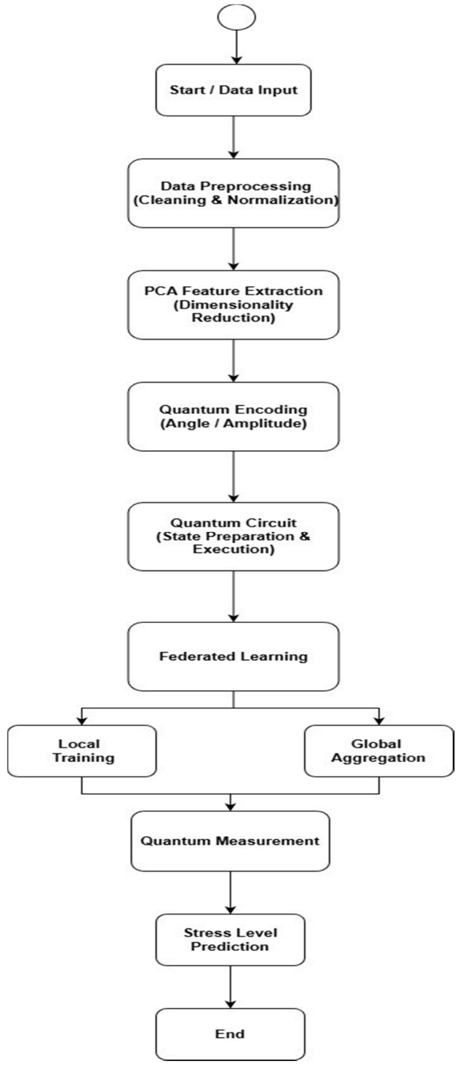

Fig. 1. Work-Flow diagram for Mental Stress Detection

partitioned into multiple subsets representing different clients. Each client trains a local quantum model independently us-ing its own data. Instead of sharing raw data, only model parameters are transmitted to a central server. The global model is updated using the Federated Averaging (FedAvg) algorithm, which aggregates local parameters to produce a unified model. The training process is performed iteratively, allowing the global model to improve with each communica-tion round. This approach ensures that sensitive data remains local while benefiting from collaborative learning. Finally, the trained model is used for prediction, where new input data is processed and classified into corresponding stress levels. The proposed methodology effectively combines the strengths of classical feature selection, quantum learning capabilities, and federated privacy mechanisms, resulting in an efficient and secure framework for mental stress detection.

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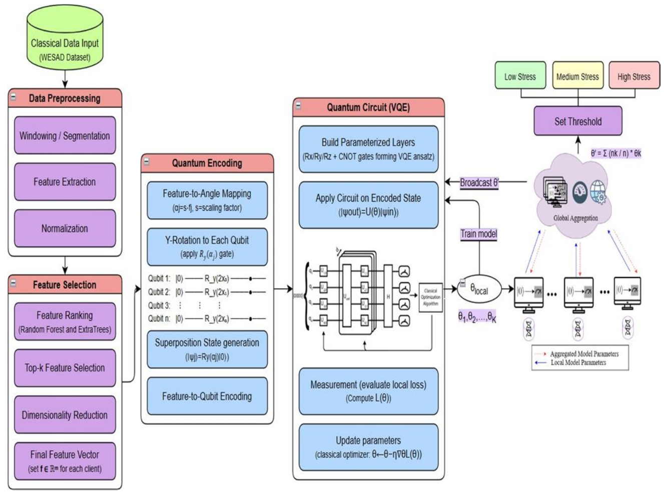

Fig. 2. System Architecture for Mental Stress Detection

IV. RESULTS AND DISCUSSION

The performance of the proposed stress classification system was analyzed using three different computational approaches: Classical Machine Learning, Quantum Machine Learning, and Federated Learning. The models were evaluated using confusion matrices, overall accuracy comparison, class dis-tribution analysis, and federated training performance across multiple epochs. The stress levels considered in the study were categorized into Low, Medium, and High classes.

A. *Classical Machine Learning Performance*

The Classical Extra Trees classifier produced the highest prediction performance among all implemented models. The model achieved an overall accuracy of 98.4%, indicating highly reliable stress classification capability. The confusion matrix demonstrates that almost all samples were correctly identified with very limited classification errors.

- The model correctly classified: 133 samples belonging to the high stress category, 386 samples belonging to the low stress category, and 90 samples belonging to the medium stress category.

Very few instances were misclassified, which confirms that the classical approach effectively learned the relationship between the extracted features and stress categories. The obtained results indicate strong model stability and excellent class separation performance.

B. *Quantum Machine Learning Performance*

The Quantum Machine Learning model achieved an accu-racy of 91.4

- According to the confusion matrix: 127 high stress samples were correctly predicted, 365 low stress samples were correctly identified, and 74 medium stress samples were accurately classified.

The model showed moderate confusion between low and medium stress classes, resulting in additional prediction errors compared to the classical approach. Nevertheless, the quantum model maintained stable classification behavior and showed potential for future intelligent healthcare systems that may utilize quantum computing resources.

C. *Federated Learning Performance*

The Federated Learning framework achieved an overall classification accuracy of 86.3

- The confusion matrix results show that: 111 high stress samples were correctly classified, 384 low stress samples were correctly predicted, and 39 medium stress samples were correctly identified.

The medium stress category experienced higher misclas-sification rates compared to other classes. This reduction in performance may be associated with decentralized parameter aggregation and variations in local training data distributions across participating nodes.

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D. System Performance Discussion

The proposed stress classification system was evaluated using Classical, Quantum, and Federated Learning models. The Classical Extra Trees model achieved the highest accuracy of 98.4

The classical model showed the best prediction perfor-mance with minimum classification errors. The quantum model provided stable results, while the federated model ensured privacy-preserving distributed learning. Dataset im-balance slightly affected medium stress classification. Overall, the system demonstrated effective and reliable stress prediction performance for healthcare monitoring applications.

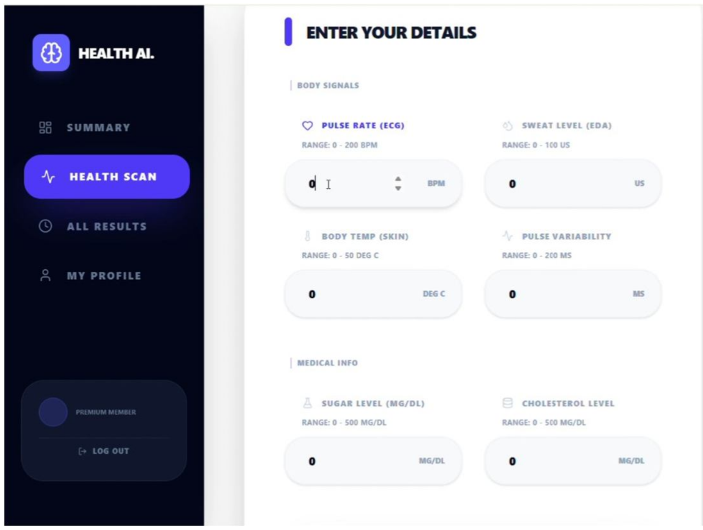

Fig. 3. Health Monitoring Interface for Real-Time Physiological Data Acquisition and Stress Assessmen

V. CONCLUSION

This study presented an intelligent stress classification system using Classical, Quantum, and Federated Learning approaches. The proposed framework successfully classified stress levels into low, medium, and high categories. Experi-mental analysis showed that the Classical Extra Trees model achieved the highest accuracy of 98.4%.

The Quantum Learning model also produced reliable pre-diction performance with 91.4 % accuracy. Federated Learn-ing achieved secure and privacy-preserving distributed model training with satisfactory results.The confusion matrix analysis confirmed effective stress prediction with minimum classifica-tion errors. Dataset imbalance slightly affected the classifica-tion of medium stress samples. The overall system demon-strated stable and efficient performance during training and testing. The proposed framework can be effectively used in future smart healthcare and real-time stress monitoring applications.

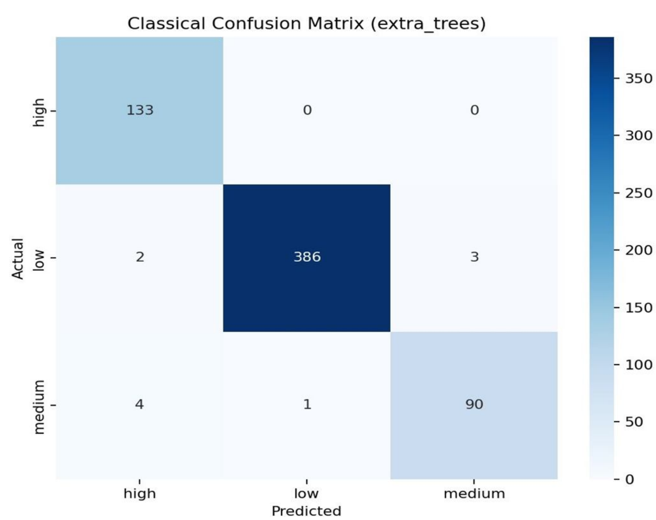

Fig. 4. Classical Confusion Matrix

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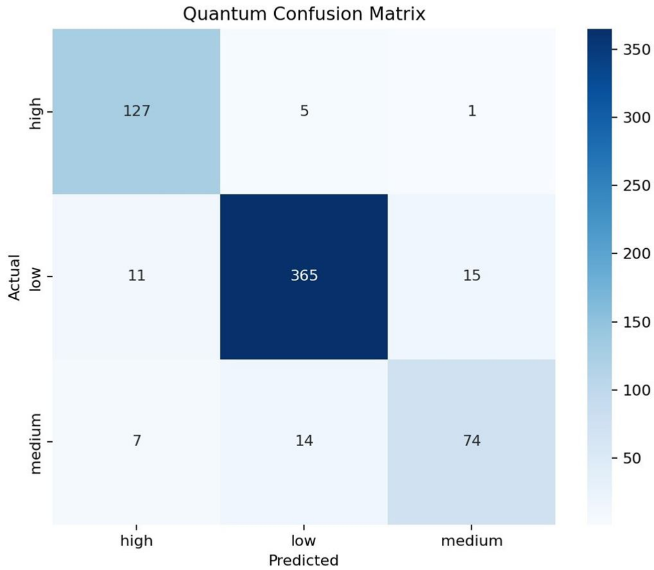

Fig. 5. Quantum Confusion Matrix

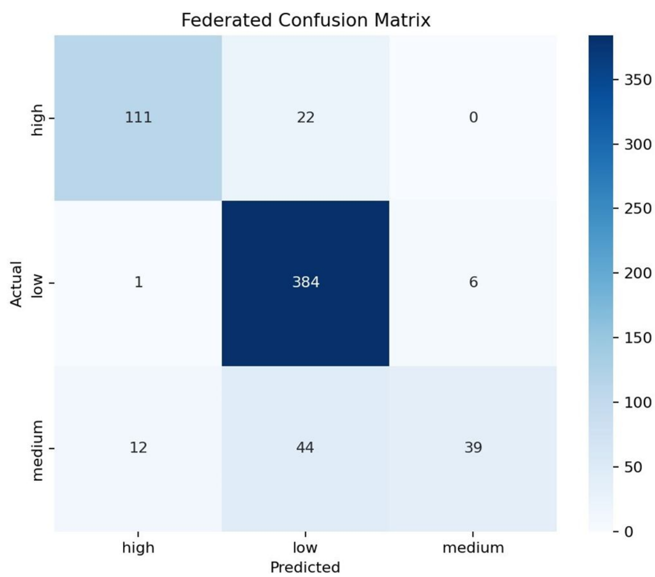

Fig. 6. Federated Confusion Matrix

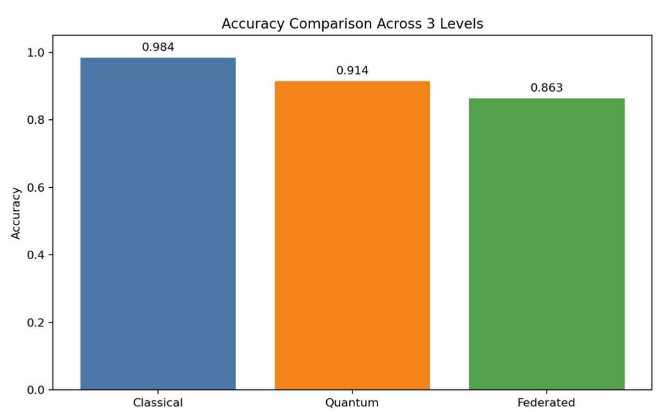

Fig. 7. Accuracy of Classical vs Quantum vs Federated

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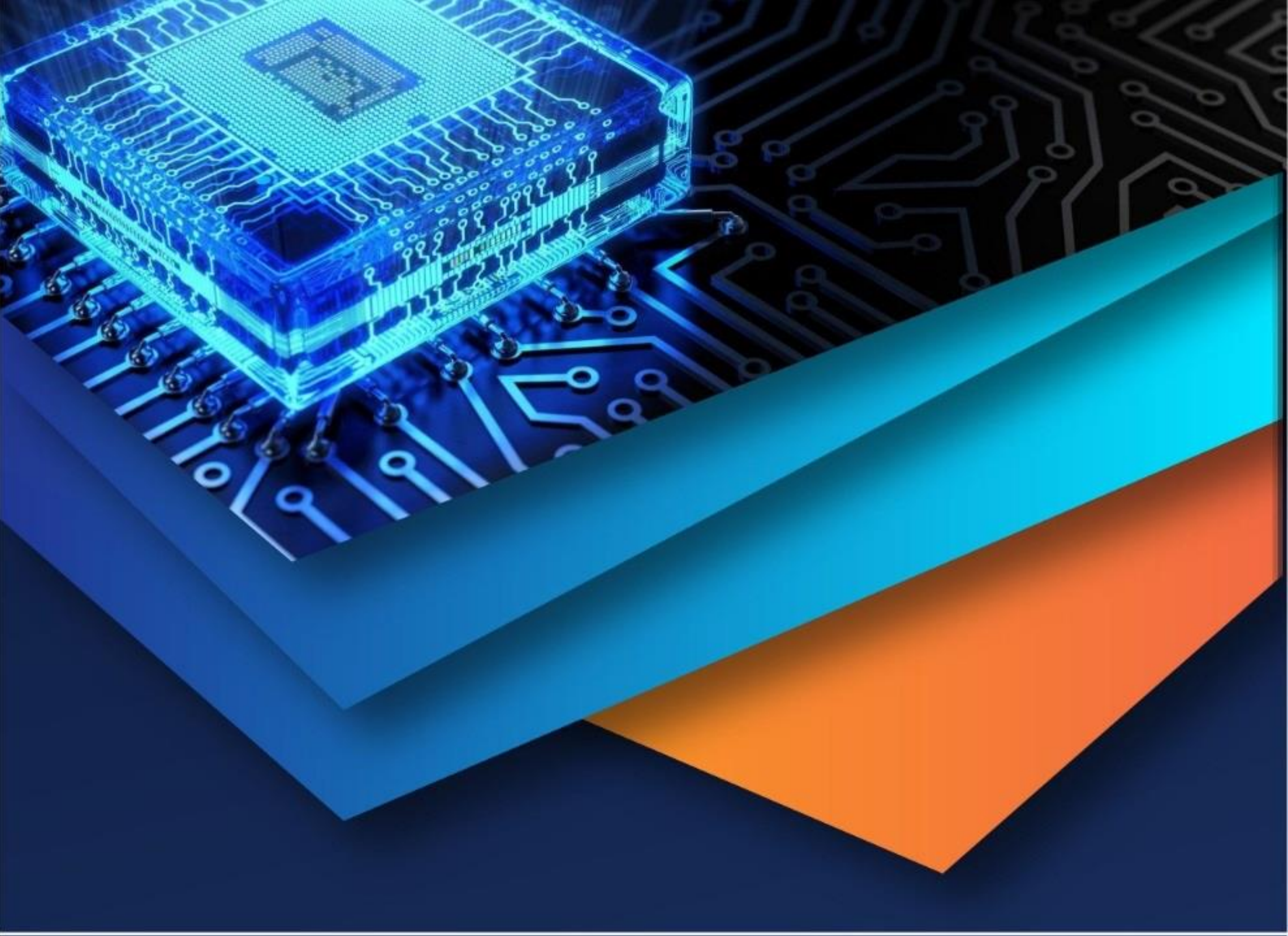

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