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Comprehensive Review on AI-Driven Medical Diagnostics: Current Trends, Techniques, and Future Directions

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Abstract: Artificial Intelligence (AI) has significantly transformed the field of medical diagnostics by improving disease detection accuracy, reducing diagnostic time, and enabling continuous patient monitoring. This review paper consolidates findings from 30 research papers published between 2001 and 2025 to map the progress in AI-based diagnostic systems. The paper focuses on five major areas: deep learning for medical imaging, IoT-enabled healthcare systems, Explainable AI (XAI), edge computing, and federated learning.

Deep learning architectures such as CNN, ResNet, U-Net, DenseNet, and CheXNet have demonstrated expert-level diagnostic performance in tasks like skin cancer detection, diabetic retinopathy classification, pneumonia detection, and brain tumor segmentation.

IoT and wearable technologies further support real-time healthcare monitoring outside clinical environments. Explainable AI improves transparency and clinician trust, while edge AI and federated learning address privacy, latency, and resource limitations in healthcare systems.

Despite significant progress, several challenges remain including class imbalance in medical datasets, interoperability issues, high computational requirements, and lack of standardization in explainable frameworks. This paper also identifies future research directions including lightweight AI models, multimodal healthcare systems, and AI deployment in low-resource environments.

Keywords: Artificial Intelligence, Deep Learning, Medical Diagnostics, Explainable AI (XAI), Federated Learning, IoT-Enabled Healthcare, Edge Computing, Convolutional Neural Networks, Wearable Systems, Medical Image Analysis

I. INTRODUCTION

Artificial Intelligence (AI) has become one of the most influential technologies in modern healthcare systems. AI-driven diagnostic models assist clinicians in disease prediction, medical image analysis, patient monitoring, and clinical decision-making. Over the last decade, deep learning and machine learning techniques have achieved remarkable performance in medical diagnosis applications [1-5].

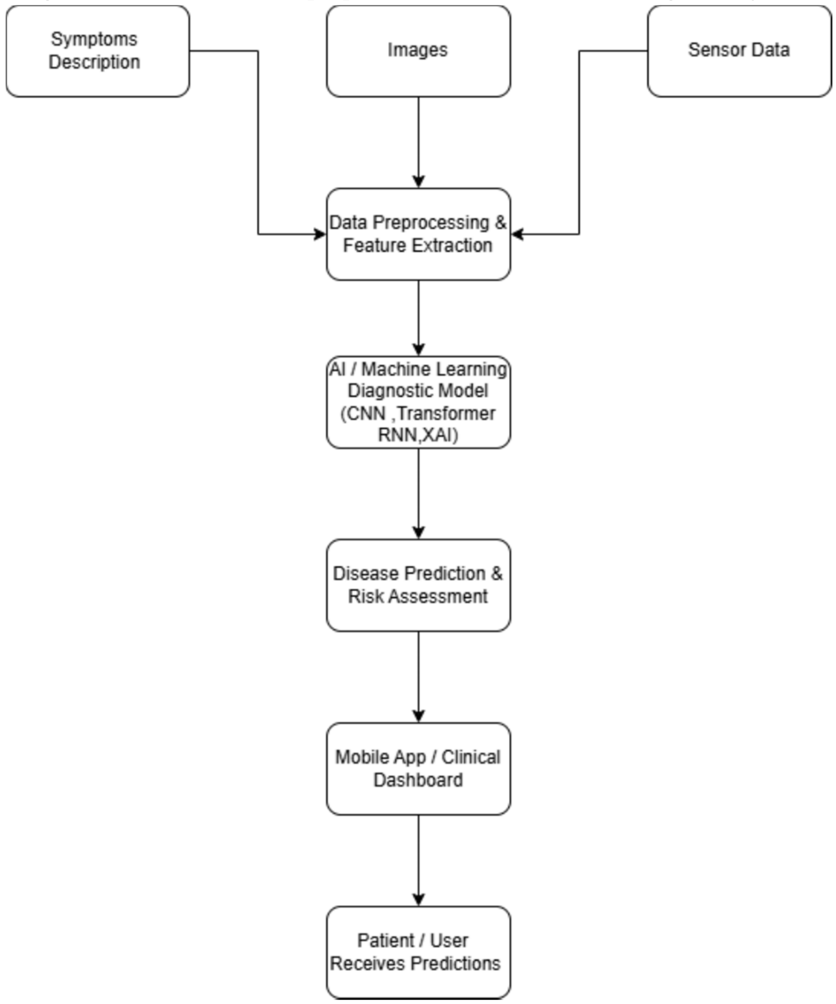
Several studies have demonstrated specialist-level diagnostic accuracy using convolutional neural networks (CNNs) and deep learning architectures.

Esteva et al. [6] achieved dermatologist-level skin cancer classification using deep neural networks, while Gulshan et al. [7] developed a deep learning system for diabetic retinopathy detection using retinal fundus images. Rajpurkar et al. [13] introduced CheXNet for automated pneumonia detection using chest X-rays.

The evolution of AI in healthcare has also expanded beyond medical imaging into wearable devices, IoT-enabled healthcare systems, electronic health records (EHRs), and explainable AI systems. Technologies such as federated learning and edge AI are now being used to improve patient privacy and reduce inference latency. This paper reviews the major advancements in AI-based medical diagnostic systems and discusses the key technologies, strengths, limitations, research gaps, and future directions in the field.

II. METHODOLOGY

Figure 1: Workflow of the proposed AI-based healthcare diagnosis system.



The smart ai diagnostic framework shows the entire flow for the design of a diagnostic tool based on ai and ml for healthcare purposes. Various sources of data are used in the framework to enable efficient diagnosis and decision-making. These include data from symptoms provided by the patient as well as medical imaging and sensor-based data.

First, healthcare data from various sources is collected. Information contained in symptoms provided by patients provides information concerning a certain condition. Medical images such as x-rays, computed tomography scans, magnetic resonance imaging, and even retinal images are some of the visual sources of information for disease detection. Also included is sensor data gathered from various health-related IoT sources such as wearables. Data from heart rate, blood pressure, oxygen levels, body temperature, and electrocardiogram is collected using sensors.

Data from all these sources is preprocessed and features extracted. In the preprocessing stage, unnecessary data, noise, and errors in the collected data are eliminated to ensure that only quality data is processed. From there, relevant features are extracted for use in diagnostic procedures.

The processed data is further subjected to analysis by means of advanced ai and ml diagnostic models. Different types of algorithms, namely convolutional neural network (CNN), recurrent neural network (RNN), transformer architecture, and XAI methods, are utilized in order to identify disease patterns and make predictive diagnoses. Convolutional neural networks prove to be effective in case of medical imaging diagnosis; RNNs excel at working with sequential health data; transformers perform excellently in learning complex relationships between variables in multimodal medical datasets. Furthermore, methods help increase the transparency of generated predictive outputs.

Based on the outputs provided by the ai models after performing the necessary calculations, disease diagnoses and risk assessments reports are generated. Such outcomes can help identify possible diseases and determine their severity level, thus helping healthcare specialists take adequate actions and intervene in a timely manner. The process of risk assessment helps prioritize individuals that require medical attention.

Lastly, the patient or end-user gains access to the diagnosis outputs, recommendations, and monitoring results through the intelligent healthcare system. Medical consultation can be conducted instantly, and the user will experience continuous health monitoring as well as enhanced user engagement. With such innovations as ai, medical images, sensors, and explainable diagnosis, the proposed framework can serve well in future smart healthcare applications that require reliable, efficient, and personalized medicine.

III. EVOLUTION OF AI IN MEDICAL DIAGNOSTICS

Early machine learning systems demonstrated the feasibility of computational diagnosis in clinical medicine. However, these systems lacked scalability and computational efficiency [18]. The introduction of deep learning architectures such as AlexNet [17], Fully Convolutional Networks (FCN) [10], ResNet [11], and U-Net [12] significantly improved diagnostic performance in medical imaging tasks.

Deep learning models enabled automated feature extraction from large medical datasets and improved disease classification accuracy. CNN-based architectures became dominant in applications such as cancer screening, pneumonia detection, retinal disease diagnosis, and medical image segmentation. Clinical success was demonstrated through landmark studies by Esteva et al. [6], Gulshan et al. [7], and Rajpurkar et al. [13], where AI systems achieved specialist-level performance.

The development of transfer learning [19], attention mechanisms [32], and recurrent neural networks such as LSTM [29] further improved AI performance in healthcare applications. Explainable AI methods were later introduced to improve transparency and clinician trust [15].

IV. DEEP LEARNING FOR DISEASE DETECTION

Deep learning has become the most widely used technology in AI-based medical diagnosis. Convolutional Neural Networks (CNNs) can automatically identify complex disease patterns in medical images [8, 9]. CNN-based systems have demonstrated strong performance in cancer screening, pneumonia detection, and diabetic retinopathy classification [6, 7, 13]. DenseNet architectures [21] and UNet++ [22] further improved segmentation and disease localization performance.

Deep learning has also been successfully applied in brain tumor segmentation [28], pancreas segmentation [31], and electronic health record analysis [23]. However, major limitations remain including dataset imbalance, annotation costs, and computational requirements [19, 20].

The training data in medicine is highly skewed — models may work well for common conditions but fail for rare diseases that often matter most. Annotating medical data is costly and requires specialist knowledge. The compute requirements for training and applying deep learning models can be prohibitive in resource-poor settings.

Key applications of deep learning in healthcare include: skin cancer classification, diabetic retinopathy detection, pneumonia diagnosis, brain tumor segmentation, lung cancer prediction, and breast cancer screening.

V. IOT AND WEARABLE-BASED SMART DIAGNOSTICS

AI-enabled IoT and wearable systems support continuous patient monitoring and real-time healthcare analysis. Wearable devices equipped with sensors can collect ECG signals, temperature data, blood oxygen levels, and other physiological parameters. Deep neural network approaches have achieved cardiologist-level arrhythmia detection using ECG signals [24]. Such systems support early disease identification and remote healthcare delivery.

Advantages of IoT-enabled healthcare systems include real-time monitoring, remote healthcare support, continuous data collection, and improved patient accessibility. However, practical deployment still faces challenges including battery constraints, sensor noise and data drift, network dependency, security and privacy concerns, and high deployment costs [27].

In many rural areas where IoT diagnostics would be most beneficial, network infrastructure remains poor — a significant concern for cloud-based inference systems. Wearables must also be recharged frequently, which is critical for continuous monitoring applications.

VI. EXPLAINABLE AI IN HEALTHCARE

Explainable AI (XAI) is essential for building clinician trust and adoption of AI-assisted medical systems [15]. Clinicians require transparency in AI predictions before adopting automated healthcare solutions. XAI techniques improve understanding of model decision-making, feature importance, disease prediction reasoning, and diagnostic confidence.

Greenspan et al. [14] highlighted the future importance of interpretable AI systems in medical imaging, while Topol [3] emphasized the collaboration between human expertise and artificial intelligence in high-performance medicine. Despite significant progress, there is still no universally accepted framework for evaluating interpretability in healthcare AI systems [5].

A well-recognized trade-off exists between model accuracy and interpretability — more accurate models tend to be less interpretable. Resolving this trade-off while maintaining clinical performance remains an active area of research.

VII. EDGE COMPUTING AND FEDERATED LEARNING

Edge computing and federated learning have emerged as important approaches for addressing privacy and latency challenges in healthcare AI systems. Federated learning enables collaborative model training across distributed hospitals without directly sharing patient data [23]. This approach improves privacy preservation and supports regulatory compliance.

Edge AI systems reduce inference latency and support deployment in low-resource settings [27]. Advantages include improved patient privacy, reduced cloud dependency, faster diagnostic response, and better support for rural healthcare systems. However, hardware limitations, communication overhead, and heterogeneous datasets remain significant challenges [5].

Edge devices are limited in the amount of memory and processing power available for complex model inference. Federated learning adds communication costs and may generate inconsistent models across different sites if the local datasets are not sufficiently similar.

VIII. MULTIMODAL HEALTHCARE SYSTEMS

Advanced diagnostic systems increasingly combine multiple data modalities such as medical imaging, wearable sensor data, and electronic health records [23]. Integrated AI systems supported by IoT technologies and cloud computing can improve diagnostic accuracy and clinical workflow efficiency [5].

Modern multimodal healthcare AI combines medical images, electronic health records, wearable sensor data, clinical notes, and IoT device outputs. These systems are considered important for future smart healthcare ecosystems that support complete clinical processes.

However, interoperability limitations, fragmented healthcare data standards, and infrastructure constraints remain major barriers to deployment [4]. Healthcare data lives in a fragmented environment of proprietary formats, standards, and institutional systems — crossing these boundaries is one of the toughest challenges for clinical AI systems.

IX. RESEARCH GAPS AND CHALLENGES

Several research gaps still exist in AI-driven medical diagnostics. Table II below presents the major challenges alongside their impacts and possible solutions.

A. Data Imbalance

Medical datasets are highly imbalanced because rare diseases have limited training samples. This is endemic to the field of medicine — severe diseases are by definition rarer — and continues to skew model performance and overestimate accuracy. Data augmentation and synthetic data generation are proposed as mitigation strategies.

B. Lack of Standardized Explainability

There is currently no universally accepted framework for evaluating explainable AI systems in healthcare. This makes it difficult to compare systems and set regulatory standards, limiting the clinical adoption of AI tools.

C. Privacy Concerns

Patient data privacy remains one of the biggest challenges in healthcare AI systems. Federated learning provides a promising solution by enabling model training without direct data sharing.

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D. Hardware Limitations

Edge devices and wearable systems often suffer from limited processing power and memory, making it difficult to run complex AI models in real-time diagnostic scenarios. Model compression techniques offer a potential pathway forward.

E. Interoperability Issues

Healthcare systems use different standards and proprietary formats, making large-scale integration difficult. Standardized healthcare APIs and data exchange protocols are needed to enable seamless AI deployment across institutions.

TABLE I: Key Strengths and Primary Limitations of AI-Driven Medical Technologies

Technology	Key Strength	Primary Limitation
Deep Learning	High diagnostic accuracy on benchmark tasks	Requires large, well-labelled datasets
IoT Systems	Enables real-time and continuous patient monitoring	Dependent on connectivity and battery life
Explainable AI	Builds clinician trust in AI-assisted decisions	No standardized frameworks for clinical contexts
Edge AI	Reduces inference latency; supports offline use	Constrained by local hardware capacity
Federated Learning	Protects patient data privacy across sites	Introduces communication overhead and non-IID challenges

TABLE II: Challenges, Impacts, and Future Directions in AI-Based Healthcare

Challenges	Impact	Possible Solution
Data Imbalance	Reduced rare disease detection	Data augmentation & synthetic data
Lack of Explainability	Low clinician trust	Explainable AI frameworks
Privacy Concerns	Restricted data sharing	Federated learning
Hardware Limitations	Poor edge deployment	Model compression
Interoperability	Integration failure	Standardized healthcare APIs
High Computational Cost	Limited rural deployment	Lightweight AI models

X. COMPARISON OF AI-BASED MEDICAL DIAGNOSTIC MODELS

Table III below provides a comparative summary of key AI-based diagnostic models and their performance across published studies, highlighting technique, application, dataset, key strength, and limitation for each model.

TABLE III: Comparison of Machine Learning Models for AI Medical Diagnostics across Published Studies

Ref / Authors	Year	Technique/Model	Application	Key Strength	Limitation
Esteva et al. [6]	2017	CNN	Skin cancer detection	High image classification	Needs large labeled datasets
Gulshan et al. [7]	2016	Deep CNN	Diabetic retinopathy	Strong ophthalmic screening	Limited generalization
Rajpurkar et al. [13]	2017	CheXNet	Pneumonia detection	Automated chest diagnosis	Dataset imbalance
De Fauw et al. [1]	2018	DL Pipeline	Retinal disease referral	Multi-stage diagnosis	High computational demand
Hannun et al. [24]	2019	Deep Neural Net	Arrhythmia detection	Real-time monitoring	Requires wearable infra.
McKinney et al. [25]	2020	AI Mammography	Breast cancer screening	High screening efficiency	Expensive deployment
Ardila et al. [26]	2019	3D CNN	Lung cancer prediction	Early-stage detection	Large compute requirements
Shickel et al. [23]	2018	DL for EHR	Clinical prediction	Handles temporal data	Privacy concerns
Federated AI [23]	2024–25	Federated AI	Multi-hospital diagnosis	Protects patient data	Communication overhead

XI. FUTURE SCOPE

Several areas appear particularly promising for future research. Hybrid AI models that combine the predictive power of deep learning with the transparency of XAI techniques would address the accuracy-interpretability trade-off that currently limits clinical trust.

Energy-efficient edge architectures drawing on developments in neuromorphic computing and model quantisation could make real-time on-device inference viable on low-cost hardware. The standardization of medical imaging and clinical record datasets, ideally through international collaborative initiatives, would enable more rigorous cross-study comparison and accelerate progress across the field.

Robust multimodal frameworks capable of reliably fusing heterogeneous data types — imaging, wearable signals, clinical notes — while tolerating missing modalities or sensor failure, deserve more systematic investigation. Finally, deployment studies in rural and low-income settings, going beyond feasibility demonstrations to longitudinal clinical evaluation, are needed to establish what AI diagnostics can actually deliver at the margins of healthcare access.

Key future research directions include: hybrid AI models combining accuracy and explainability; lightweight edge AI systems for rural healthcare; energy-efficient neuromorphic computing architectures; standardized international medical datasets; robust multimodal healthcare frameworks; and real-world deployment studies in low-resource settings.

XII. CONCLUSION

AI-powered diagnostics have progressed far beyond the proof-of-concept stage. Over the last decade, deep learning systems have achieved expert-level performance in a vast range of imaging-related tasks. At the same time, the growing use of wearable devices and IoT technologies has enabled continuous health monitoring outside traditional clinical environments.

Despite these advances, a clear gap still exists between experimental results and real-world clinical deployment. Interpretability, scalability, integration, and performance in resource-constrained environments are among the key challenges. Overcoming these challenges will require not only technical advances but also improved communication between AI researchers, clinicians, and regulatory bodies.

The integration of AI, IoT, edge computing, and federated learning technologies has the potential to transform global healthcare systems and improve medical accessibility worldwide. Future systems must focus not only on accuracy but also on safety, affordability, transparency, and real-world clinical applicability.

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4) Review and Editing: Prof. Dr. Sachin Takale , Shivam Devkar
5) Supervision: Prof. Dr. Sachin Takale

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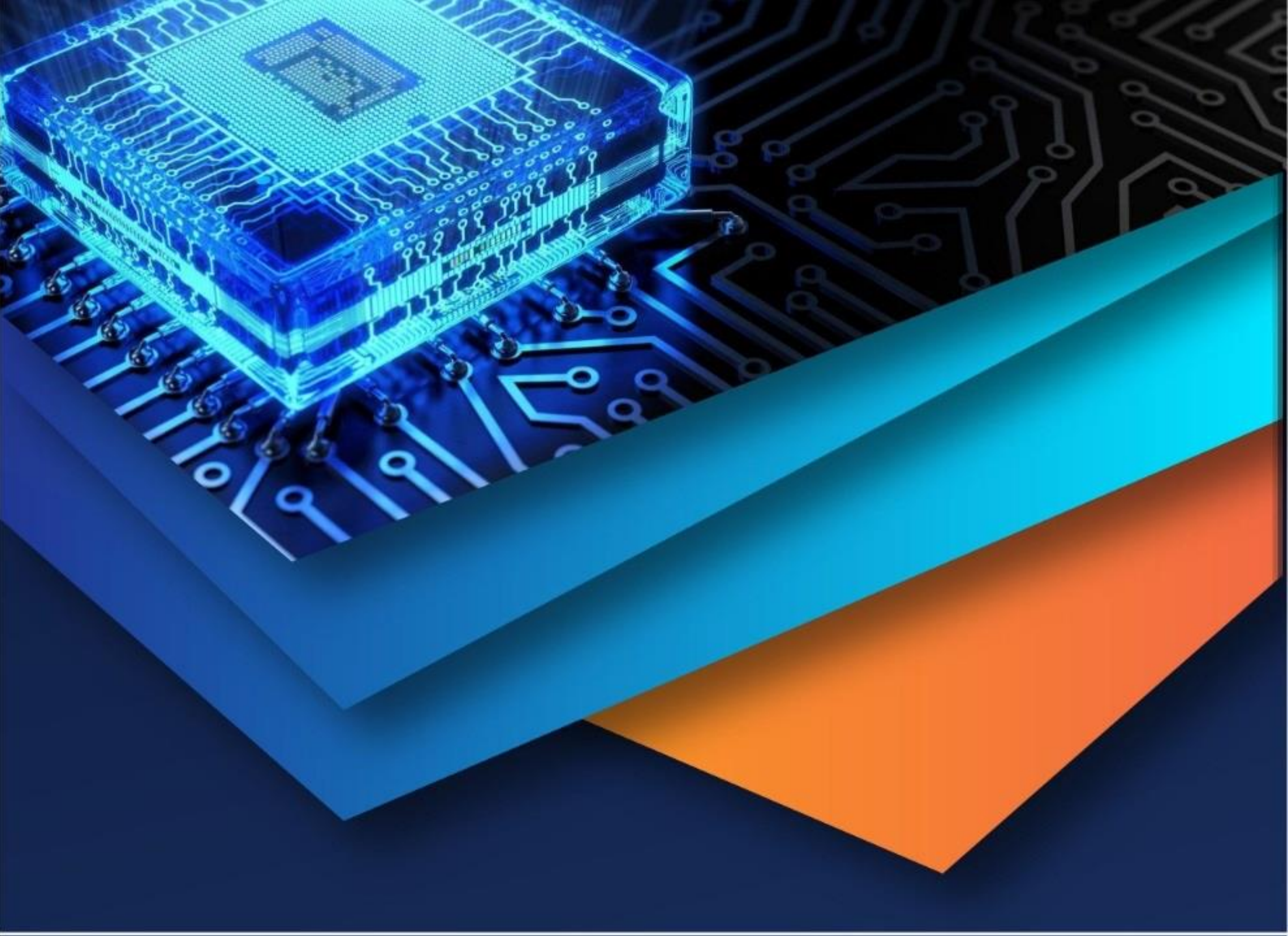

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