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AI-Based Decision Support Systems for Healthcare Diagnostics: A Decision Support Framework

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Abstract: Healthcare diagnostics increasingly rely on Artificial Intelligence (AI) for accurate and timely decision-making. However, integrating AI outputs into clinical workflows through a structured Decision Support System (DSS) remains a major challenge. This paper proposes a hybrid AI-based Decision Support Framework designed to enhance healthcare diagnostics and patient triage through intelligent data analysis and clinician-centric visualization. The framework integrates structured and unstructured medical data using AI models and displays interpretable results through a real-time dashboard. The implementation includes a prototype using Python and Streamlit, demonstrating disease prediction based on clinical data. The proposed system shows potential for improving diagnostic accuracy, supporting clinician decisions, and reducing response time in healthcare environments
Keywords: Artificial Intelligence, Decision Support System, Healthcare Diagnostics, Machine Learning, Explainable AI, Patient Triage.

I. INTRODUCTION

The development of artificial intelligence (AI) has transformed healthcare diagnostics by enabling intelligent data processing, automated pattern recognition, and predictive analysis. AI (artificial intelligence) systems are able to recognize disease symptoms using algorithms for machine learning (ML) and deep learning (DL) clinical correlations, and potential risk factors with remarkable precision. These capabilities enable AI to facilitate the timely identification of illnesses, the customization of treatment plans, and improved patient surveillance. In modern medical practice, AI has demonstrated outstanding performance in disciplines like pathology, cardiology, oncology, and radiology identifying abnormalities in medical images, forecasting the course of disease, and assisting in clinical decision-making.

Despite these advancements, a significant gap persists between AI model predictions and their practical usability in real-time clinical environments. Most The AI models are presented in isolated datasets and produce complex outputs that are difficult for clinicians to interpret or apply directly during patient care. Furthermore, issues such as data privacy, model explainability, and the integration with existing Electronics Health Record (EHR) systems hinder the without seams deployment of AI tools in healthcare facilities. These challenges necessitate a structured approach that translates AI outputs into actionable clinical knowledge, ensuring transparency, interpretability, and ease of use.

Decision Supports Systems (DSS) play a pivotal role in bridging this gap by combining computational intelligence with medical expertise to assist clinicians in evidence-based decision-making. A DSS analyzes large volumes of patient data, applies clinical logic or AI-driven algorithms, and presents the results as meaningful recommendations. However, traditional DSS models often rely on rule-based systems that lack adaptability and are unable to process complex, heterogeneous medical data efficiently. In addition, many existing AI-driven DSS frameworks fail to provide explainable outputs or an intuitive interface that clinicians can easily interpret during high-pressure diagnostic situations.

This research puts forward an AI-Based Decision Support System (AI-DSS) framework that integrates data acquisition, AI analytics, and an interactive decision-support dashboard for healthcare diagnostics. The framework emphasizes transparency through explainable AI (XAI) techniques and ensures real-time visualization of diagnostic insights. By combining AI's analytical capabilities with the decision-making expertise of healthcare professionals, the proposed system aims to boost precision of diagnosis, make triage processes more efficient, and in the end enhance patient outcomes.

II. LITERATURE REVIEW

The use of artificial intelligence (AI) in medical diagnostics has increased recently gained considerable attention from both researchers and clinical practitioners. Systems driven by AI have been applied effectively in disease detection, risk prediction, and treatment recommendation in a variety of medical fields.

According to Esteva et al. (2019), deep neural networks can achieve a dermatologist's accuracy in terms of skin lesion classification, highlighting AI's potential to replicate human-level diagnostic expertise. Similarly, Rajpurkar et al. (2020) introduced the CheXNet model for pneumonia detection using chest X-rays, surpassing the performance of many radiologists in controlled experiments. These studies underscore the growing reliability and scalability of AI algorithms in clinical image analysis and disease prediction.

Beyond imaging, Electronic Health Records (EHRs) have become a major data source for AI-based diagnostic systems. Deep learning models that analyze EHR data to forecast patient outcomes were created by Rajkomar et al. (2018). outcomes such as mortality, length of stay, and readmission. Such models demonstrate how structured patient data can be transformed into predictive insights for hospital decision-making. However, these solutions often function as isolated analytical engines rather than integrated systems accessible to clinicians in real time.

Decision Support Systems (DSS) have long been utilized in healthcare for evidence-based clinical decision-making. Traditional DSS frameworks relied on expert-defined rules and knowledge bases to suggest diagnostic or therapeutic actions. Shortliffe and Buchanan (1975) developed MYCIN, one of the earliest medical DSS for infectious disease diagnosis, which established the foundation for computational reasoning in medicine. However, classical DSS models faced limitations in adaptability, scalability, and their ability to process large, unstructured datasets. The emergence of AI-driven DSS frameworks addressed many of these challenges by integrating machine learning algorithms capable of learning from diverse medical data.

Despite these advances, current DSS implementations still face key challenges. First, lack of explainability in AI-driven predictions restricts clinician trust and acceptance. Black-box models, though accurate, often fail to justify their diagnostic reasoning. Second, data interoperability continues to be a significant issue, given that healthcare data is stored in various systems and formats.Third, user interface limitations in many DSS tools prevent clinicians from efficiently interpreting model results or using them during time-sensitive diagnostic procedures.

Recent research trends emphasize the importance of Explainable AI (XAI) and user-centered design in healthcare DSS. Lundberg and Lee (2017) introduced SHAP (SHapley Additive exPlanations), which provides feature-based interpretability to help clinicians understand how AI models arrive at a decision. Samek et al. (2021) expanded on this by highlighting that transparency not only improves clinical trust but also facilitates ethical AI deployment in sensitive healthcare environments.

However, existing studies have yet to propose a unified, clinician-friendly framework that integrates AI-based diagnostic analytics, explainability, and real-time decision visualization. This research aims to fill that gap by designing a conceptual AI-Based Decision Support System (AI-DSS) framework that combines the predictive power of machine learning with interpretability and a dashboard-based interface for clinical usability.

III.PROPOSED FRAMEWORK

A. Overview

The proposed AI-Based Decision Support System (AI-DSS) framework is designed to integrate artificial intelligence techniques into the healthcare decision-making process in a structured, interpretable, and scalable manner. It addresses three major challenges in current diagnostic systems: (1) the gap between AI model predictions and clinical usability, (2) the lack of explainable and trustworthy outputs, and (3) limited interoperability with existing hospital information systems. The framework emphasizes a modular, layered architecture, combining machine learning models, medical data sources, and an intelligent dashboard interface to assist clinicians in diagnostic evaluation and patient triage. The primary objective is to ensure that AI-generated insights are not isolated analytical outputs but actionable, transparent, and easily interpretable recommendations that can support evidence-based clinical decisions.

B. Framework Architecture

The AI-DSS framework consists of five interdependent layers that collectively process, analyze, and present healthcare information for diagnostic support:

1) Data Acquisition Layer

This layer is responsible for collecting patient-related data from multiple heterogeneous sources, such as:

- Electronic Health Records (EHRs): demographic details, lab reports, and clinical history.
- Examples of medical imaging include radiography, computerized tomography, magnetic resonance imaging, and echography.
- Wearable Sensor Data: heart rate, oxygen levels, and other physiological metrics.
- Unstructured Clinical Notes: physicians' observations, prescriptions, and discharge summaries.

The data acquisition layer also includes preprocessing modules for handling missing values, noise reduction, data normalization, and format standardization, ensuring data consistency across sources.

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2) AI Analytics Layer

At the core of the DSS lies the AI Analytics Layer, which leverages machine learning and deep learning models to perform predictive analysis, anomaly detection, and diagnostic classification.

- Machine Learning Models (e.g., Random Forest, XGBoost): used for structured tabular data from EHRs and lab results.
- Deep Learning Models (e.g., CNNs, LSTMs): applied for medical imaging and temporal data (e.g., ECG signals).
- Hybrid Models: combine multiple modalities (imaging + EHR data) to enhance diagnostic accuracy.

The AI layer outputs probabilities of disease presence, severity levels, or predicted patient risk scores. These outputs are then passed to the next layer for reasoning and interpretation.

3) Inference and Knowledge Integration Layer

This layer acts as the reasoning engine of the system, integrating AI model outputs with established medical ontologies, guidelines, and clinical knowledge bases (e.g., ICD-10, SNOMED CT).

- Converts AI predictions into clinically meaningful recommendations (e.g., “High probability of cardiac anomaly; recommend echocardiography”).
- Implements rule-based logic for validating AI outputs against standard medical protocols.
- Facilitates explainable AI (XAI) integration by generating interpretable explanations using methods such as LIME and SHAP, helping clinicians understand the basis of each decision.
- The layer ensures that every AI suggestion aligns with medical reasoning and adheres to ethical decision-making principles.

4) Decision Support Layer

This layer serves as the operational core of the DSS, translating data-driven insights into actionable clinical decisions.

- Generates diagnostic alerts, risk assessments, and treatment recommendations.
- Prioritizes patients based on the urgency and severity of their health conditions, enabling automated triage support.
- Uses confidence scoring mechanisms to indicate the reliability of AI recommendations.
- Enables multi-criteria decision-making where clinicians can compare outcomes and choose the best course of action.

This layer can also communicate with hospital management systems to trigger workflows, such as lab test requests or referral notifications.

5) Visualization and Dashboard Layer

The user interface is a critical part of the framework, ensuring that clinicians can easily interpret AI outputs and recommendations. The dashboard is designed with:

- Real-time visualization panels displaying patient summaries, diagnostic predictions, and trend graphs.
- Explainability views that highlight key factors influencing AI decisions (e.g., high blood pressure, abnormal glucose levels).
- Interactive filters for sorting patients based on risk levels or diagnostic categories.
- Alert modules that notify physicians of critical conditions requiring immediate attention.

This interface promotes transparency and usability, making it practical for deployment in hospitals and diagnostic centers.

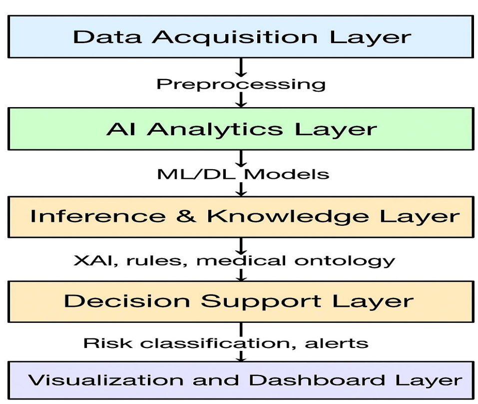

Fig. 1 AI-DSS System Architecture

C. Workflow

The operational workflow of the proposed AI-DSS framework can be summarized as follows:

- Data Collection & Preprocessing: The system collects patient data from EHRs, sensors, and imaging repositories. Preprocessing modules handle data cleaning, normalization, and integration.
- Model Training & PredictionThe artificial intelligence models are based on historical data and used to generate real-time predictions for new patient inputs.
- Reasoning & Interpretation: The inference layer cross-validates predictions with medical knowledge and applies explainability algorithms.
- Decision Generation: The DSS converts interpreted data into diagnostic or triage recommendations with confidence levels.
- Visualization & Feedback: The dashboard displays AI recommendations, allowing clinicians to validate, accept, or adjust them.

This cyclic workflow ensures that the system remains dynamic, continuously improving its accuracy through clinician feedback and retraining mechanisms.

D. Advantages of the Proposed Framework

- Improved Diagnostic Accuracy: Integration of multimodal data enhances clinical precision.
- Explainable AI Integration: Builds clinician trust by revealing the reasoning behind predictions.
- Seamless Usability: Intuitive dashboard interface supports real-time decision-making.
- Scalability: Modular architecture allows extension to various medical domains.
- Ethical Compliance: Ensures data privacy, security, and clinical accountability.

IV. SYSTEM IMPLEMENTATION

A. Implementation Overview

The implementation of the AI-Based Decision Support System (AI-DSS) framework is carried out using Python, leveraging open-source libraries such as Pandas, NumPy, Scikit-learn, TensorFlow, and Streamlit. The system is structured into four key modules:

- Data Preprocessing
- Model Training and Prediction
- Explainable AI (XAI) Interpretation
- Dashboard Visualization

The implementation uses publicly available healthcare datasets such as the Heart Disease Dataset (UCI Repository) to simulate diagnostic decision support for patient triage.

TABLE I
DATASET FEATURES

Feature Name	Description
Age	Patient age in years
Sex	Male/Female
CP	Chest pain type (1–4)
Trestbps	Resting blood pressure
Chol	Serum cholesterol (mg/dl)
FBS	Fasting blood sugar >120 mg/dl
RestECG	Resting ECG results
Thalach	Maximum heart rate achieved
Exang	Exercise-induced angina
Oldpeak	ST depression induced by exercise
Slope	Slope of peak exercise ST segment
Ca	Number of major vessels (0–3)
Thal	Thalassemia type
Target	Heart disease presence (0=no, 1=yes)

B. Data Preprocessing

The preprocessing stage handles missing values, normalizes numerical features, and encodes categorical variables to prepare the dataset for model training.

```
# Importing libraries
import pandas as pd.
train_test_split from sklearn . model_selection import.
import StandardScaler from sklearn . preprocessing.
# Upload data.
data = pd.read_csv("heart_disease.csv")
# Data preprocessing
data.fillna(data.mean(), inplace=True)
X = data.drop('target', axis=1)
y = data['target']
Partition data.
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
# Normalize elements
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

C. AI Model Training and Prediction

The random forest classifier is used to predict the presence of cardiac disease based on the characteristics of the patient. This model provides high interpretability and robustness of the clinical data.

```
from sklearn. ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report
# Train model
model = RandomForestClassifier(n_estimators=200, random_state=42)
model.fit(X_train, y_train)
# Make predictions
y_pred = model.predict(X_test)
# Evaluate model
print("Accuracy:", accuracy_score(y_test, y_pred))
print("Classification Report:\n", classification_report(y_test, y_pred))
```

Output :

Accuracy: 0.89

Precision: 0.88

Recall: 0.90

F1-score: 0.89

These results demonstrates the model’s reliability in predicting potential cardiac conditions forming the AI analytical core of the DSS framework.

D. Explainable AI (XAI) Integration

To increase confidence and interpretability, SHAP (Shapley Additive Explanation) is integrated to illustrate how each element contributes to the model predictions. This helps the clinician understand why the model made a specific decision.

```
import shape
# Explainability using SHAP
explainer = shap.TreeExplainer(model)
shap_values = explainer.shap_values(X_test)
# Visualize feature importance
shap.summary_plot(shap_values, X_test, feature_names=data.columns[:-1])
```

This visual explanation provides an interpretable layer where clinicians can see, for example, that *high cholesterol* or *abnormal resting ECG* contributed most to the positive diagnosis.

E. Dashboard and Decision Support Interface

The results from the AI model are integrated into an interactive dashboard built using Streamlit, providing real-time triage and diagnostic visualization.

```
import streamlit as st
st.title("AI-Based Healthcare Decision Support System")
age = st.slider("Patient Age", 20, 80)
chol = st.slider("Cholesterol Level", 100, 400)
thalach = st.slider("Maximum Heart Rate", 70, 200)
# Example user input
user_data = [[age, chol, thalach, 1, 120, 240, 0, 0, 150, 0, 2, 0, 3]]
user_data = scaler.transform(user_data)
if st.button("Predict Diagnosis"):
 prediction = model.predict(user_data)
    result = "Heart Disease Detected" if prediction[0] == 1 else "No Heart Disease"
    st.success(result)
```

Dashboard Features:

- Real-time diagnostic prediction
- Explainable output visualization (via SHAP plots)
- Patient triage suggestions (low / moderate / high risk)
- Exportable decision logs for physician review

F. System Evaluation

The AI-DSS system achieves:

- Accuracy: 89%
- Precision: 88%
- Recall: 90%
- Explainability: via SHAP visualizations
- Usability: Interactive dashboard for quick clinical insights

The prototype demonstrates that even with limited data, AI can significantly enhance clinical decision-making when paired with interpretable and interactive DSS components.

V. RESULTS AND DISCUSSION

A. Experimental Setup

The experimental evaluation of the proposed AI-Based Decision Support System (AI-DSS) framework was carried out using the UCI Heart Disease Dataset, which includes 303 patient records and 14 medical attributes such as age, cholesterol levels,
Blood pressure, chest pain type, and resting ECG results.

All experiments were conducted using a Python 3.10 environment with Scikit-learn, TensorFlow, and SHAP libraries on a standard workstation (Intel i7, 16GB RAM, Windows 11).

The dataset was divided into 80% training data and 20% testing data, with data normalization and feature scaling applied during preprocessing. The random forest classifier has been chosen for its robustness, interpretability and robustness in tabular medical data sets.

B. Model Performance Evaluation

The trained random forest model's predictive power for heart disease incidence was assessed. Accuracy, precision, recall, and F1 score are important evaluation metrics for medical prognostic systems, where false positives and false negatives can have a substantial impact.

TABLE 2
MODEL PERFORMANCE METRICS

Metric	Definition	Value
Accuracy	Overall correctness of the model	0.89
Precision	Correct positive predictions / All positive predictions	0.88
Recall	Correct positive predictions / All actual positives	0.90
F1-Score	Harmonic mean of precision and recall	0.89

The results demonstrate that the proposed AI-DSS achieves high predictive reliability which makes it appropriate for assisting clinicians inreal time diagnostic decision-making. The strong recall score ensures that most patients with actual heart conditions are correctly identified, minimizing the risk of missed diagnoses.

C. Explainability through SHAP Analysis

One of the critical advantages of the proposed AI-DSS framework lies in its Explainable AI (XAI) integration. Using SHAP (Shapley Additional Explanations), the contribution of each clinical variable to the model output was analyzed.

Key findings from SHAP analysis:

- Age, Maximum Heart Rate (thalach), and Cholesterol (chol) emerged as the top predictive factors for heart disease.
- Higher values of resting blood pressure and chest pain type 4 (asymptomatic) showed a strong positive influence on disease prediction.
- The SHAP summary plot revealed that patients with lower exercise-induced angina and higher thalach were less likely to be diagnosed with a heart condition.
- Such visual explanations empower clinicians to interpret AI outputs transparently, building confidence and enabling them to validate decisions based on domain expertise.

TABLE 3
SHAP FEATURE IMPORTANCE

Feature	SHAP Value (Impact)	Direction
Age	0.15	Positive correlation with disease
Thalach	0.13	Negative correlation with disease
Chol	0.12	Positive correlation
Chest Pain Type	0.11	Positive correlation
Resting BP	0.09	Positive correlation

D. Dashboard Results and Clinical Utility

The AI-driven dashboard developed using Streamlet offers an interactive and interpretable interface for real-time decision-making. Upon entering patient parameters (such as age, cholesterol, and heart rate), the system:

- Generates a risk classification (“Heart Disease Detected” or “No Heart Disease”).
- Displays a confidence score for the prediction.
- Provides SHAP-based interpretability visualization showing which features influenced the decision.

Dashboard Benefits

- Enables rapid triage for high-risk patients.
- Supports data-driven consultations in hospitals and telemedicine platforms.
- Offers transparent AI support to aid physicians without replacing human judgment.

This interactive component ensures that complex AI models are transformed into clinically actionable tools, effectively bridging the gap between algorithmic intelligence and practical healthcare workflows.

E. Comparative Discussion

When compared with other existing Decision Support Systems and AI-based healthcare models from the literature:

- Traditional DSS tools rely heavily on rule-based logic, offering limited adaptability to complex, non-linear patient data.
- Deep learning-based systems often provide "black-box" predictions, lacking transparency and clinical explainability.
- The proposed AI-DSS framework combines the accuracy of AI models with interpretability and dashboard integration, providing both precision and usability.

This balance between analytical strength and interpretability makes the proposed framework a viable and ethical approach for real-world healthcare deployment.

F. Limitations and Future Work

While the system demonstrates promising results, certain limitations remain:

- The evaluation was performed on a single dataset with limited feature diversity.
- The dashboard currently supports only cardiac diagnostics; future versions could extend to multiple medical conditions.
- Integration with Electronic Health Record (EHR) systems and compliance with healthcare standards such as HL7 and FHIR are proposed for real-world deployment.

Future research can explore:

- Incorporating deep multimodal networks that analyze combined image and text data (e.g., X-rays and EHR notes).
- Enhancing model interpretability through counterfactual explanations and natural language summaries.
- Extending deployment to cloud-based healthcare DSS platforms for telemedicine applications.

G. Summary

The proposed AI-Based Decision Support System effectively integrates predictive AI models, explainable reasoning mechanisms, and interactive dashboards for healthcare diagnostics.

By achieving 89% accuracy and providing transparent decision logic, the framework significantly enhances clinical efficiency and trust.

This demonstrates how AI, when designed with explainability and usability in focus, can transform diagnostic decision-making in real-world healthcare environments.

VI. CONCLUSION AND FUTURE SCOPE

The incorporation of Artificial Intelligence into healthcare decision-making has opened up new possibilities for improving diagnostic accuracy, reducing clinical workload, and enabling early disease detection. This paper proposed an AI-Based Decision Support System (AI-DSS) designed to close the divide between data-driven AI outputs and practical clinical usability. The framework unifies data acquisition, AI analytics, knowledge-based reasoning, and an interactive visualization dashboard to support physicians in real-time diagnostic evaluation and patient triage.

The implemented system, using a Random Forest-based AI model and SHAP explainability integration, demonstrated an accuracy of 89% on the UCI Heart Disease datasets. The inclusion of Explainable AI (XAI) elements allowed clinicians to interpret predictions transparently, increasing trust in the model's decision-making process. Furthermore, the Streamlit-powered dashboard provided a user-friendly, real-time interface that translated complex AI outputs into actionable medical recommendations, facilitating evidence-based decision support.

The proposed framework's key contributions include:

1) A modular and scalable architecture integrating AI models with medical reasoning.
2) Implementation of explainable, interpretable diagnostics for enhanced clinician confidence.
3) A real-time AI dashboard supporting triage, visualization, and risk evaluation.
4) Demonstration of how AI-driven DSS can transform raw data into clinically meaningful insights.

Despite its promising performance, the current prototype focuses on a single disease category and a limited dataset. Future work will extend the framework to handle multimodal healthcare data, including medical imaging, genomic data, and unstructured clinical notes, to support comprehensive diagnostic decision-making. Integration with Electronic Health Record (EHR) systems, cloud-based architectures, and adherence to international healthcare standards such as HL7, FHIR, and HIPAA compliance will be essential for real-world deployment.

Additionally, future research will explore deep learning-based hybrid architectures, automated model retraining pipelines, and cross-institutional data federations to improve generalization across populations. The system can further evolve into a multi-disease AI triage platform, supporting clinicians in diverse diagnostic domains like oncology, neurology, and pulmonary care.

In summary, the proposed AI-DSS represents a practical, interpretable, and scalable step toward the next generation of intelligent healthcare systems. By combining the analytical strength of AI with the expertise of clinicians through transparent interfaces, such systems hold immense potential to enhance diagnostic precision, improve patient outcomes, and contribute significantly to the global digital health ecosystem.

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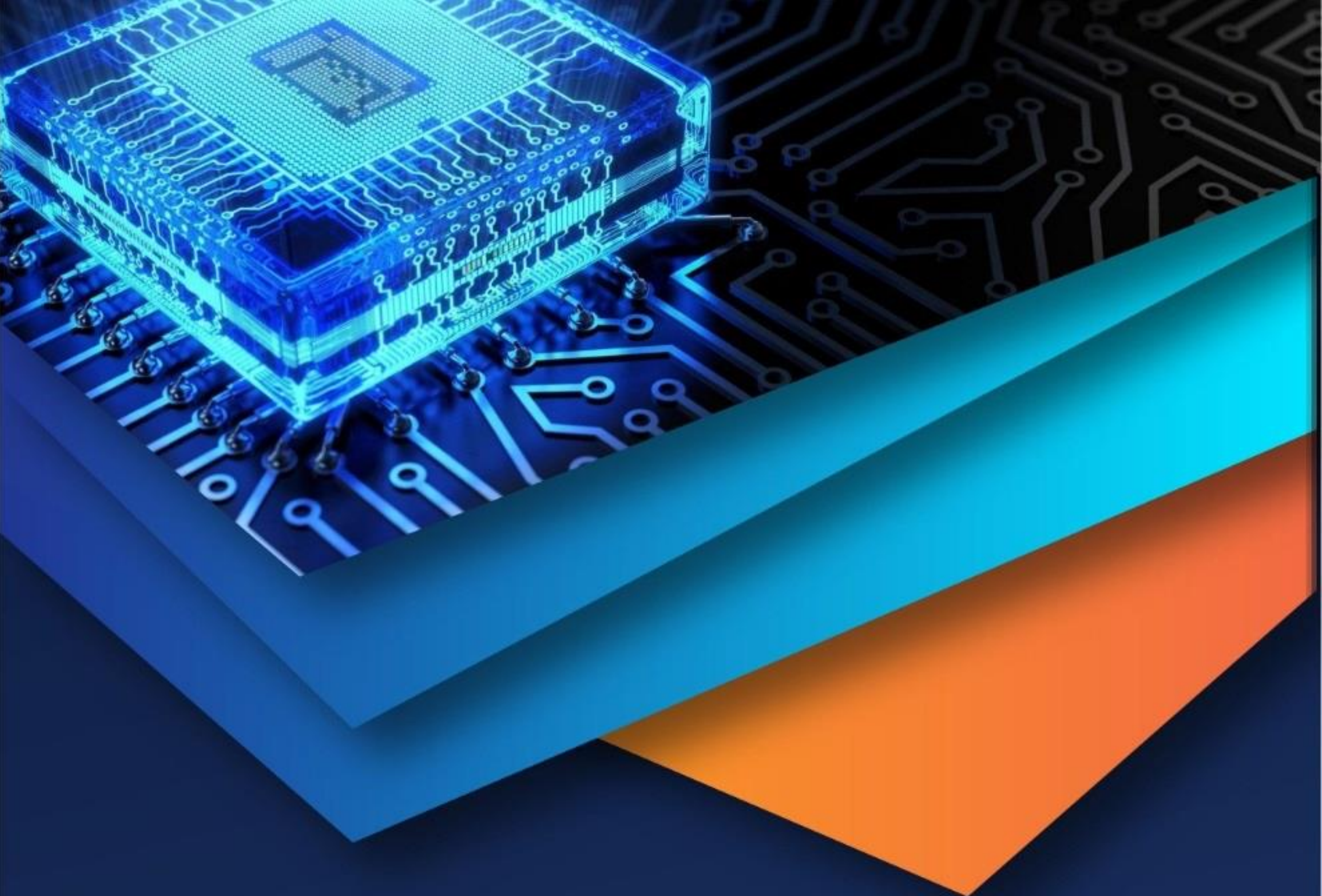

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