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Predictive Forecasting for Early Risk Detection in Smart Healthcare Systems using AI

Tamanna Maner
ME-II Computer Department KJ College of Engineering and Management Reseach, Pune, India

Abstract: The rapid growth of artificial intelligence (AI) has transformed modern healthcare by enabling predictive analysis and early detection of medical risks. Traditional health monitoring systems primarily offer reactive alerts based on threshold violations, often failing to identify hidden patterns in physiological signals such as ECG, blood pressure, glucose levels, and kidney function indicators. To address these limitations, AI-driven predictive forecasting models— particularly LSTM, GRU, CNN, and Transformer-based architectures—have emerged as powerful tools for analyzing time-series health data and forecasting potential risks before they occur. This survey paper reviews state-of-the-art research, existing methodologies, datasets, and machine learning techniques used for early health risk prediction. The paper highlights trends, compares model performance, identifies current research gaps, and emphasizes the need for proactive, data-driven healthcare systems. The findings suggest that AI- based forecasting can significantly improve timely intervention, reduce medical emergencies, and enable personalized patient care.
Keywords: AI in Healthcare, Predictive Forecasting, Early Risk Detection, Time-Series Analysis, LSTM, Transformers, Smart Healthcare Systems, Medical Deep Learning.

I. INTRODUCTION

The integration of Artificial Intelligence (AI) into healthcare has initiated a major shift from traditional reactive medical practices toward proactive, data-driven healthcare systems. Today, most clinical monitoring solutions rely on threshold- based alert mechanisms, where abnormalities in vital signs—such as elevated blood pressure, abnormal ECG rhythms, rising glucose levels, or declining kidney function—are detected only after the condition has already progressed. Such reactive systems fail to capture early warning patterns, time-dependent fluctuations, and subtle physiological trends that could indicate the onset of critical health disorders. With the growing availability of electronic health records, wearable sensors, biomedical signals, and large-scale medical datasets, AI-based predictive forecasting has emerged as a promising direction for early risk detection.

Predictive forecasting models leverage time-series machine learning and deep learning techniques, including LSTM, GRU, CNN, and Transformer architectures, to analyze historical health data and forecast possible future health deterioration. These models learn the underlying temporal relationships, identify hidden health patterns, and estimate the probability of upcoming risks such as cardiac irregularities, hypertension crises, diabetic spikes, and kidney abnormalities. As a result, healthcare providers can intervene earlier, reduce emergency incidents, personalize treatment plans, and improve patient outcomes.

This survey paper presents a comprehensive review of existing predictive healthcare systems, highlighting current methodologies, AI algorithms, datasets, challenges, and research gaps. It aims to provide insights into how forecasting-based AI systems can transform smart healthcare from simple monitoring to intelligent, preventive healthcare management. By critically analyzing existing research and identifying limitations, this paper establishes the need for advanced, accurate, and scalable AI-driven forecasting systems for early health risk detection.

II. LITERATURE SURVEY

Early detection of clinical and neurodegenerative disorders has seen rapid progress through data-driven models that fuse domain knowledge, multimodal inputs, and generative augmentation. The papers surveyed below span interpretable temporal models for electronic health records, generative- data-augmented classifiers for oncology, VAE-based multimodal fusion for cardiac screening, deep representation learning for speech-based dysarthria detection, and handwriting-kinematics analysis for Alzheimer's screening. Together they highlight recurring themes: (1) balancing predictive power and interpretability, (2) addressing class imbalance via generative models or resampling, and (3) leveraging multimodal or learned representations for robust early-warning systems. Representative works and methodological details follow.

A. EvolveFNN — Interpretable longitudinal EHR modeling (2025)

EvolveFNN proposes an interpretable recurrent-fuzzy framework designed to learn human-readable rules from longitudinal electronic health records while retaining the temporal modeling capacity of RNNs. The architecture fuses fuzzy neural network (FNN) modules with recurrent units (e.g., GRU/LSTM variants) so that evolving fuzzy-rule weights encode temporal dynamics. Training uses gradient- based optimizers with specialized regularization for membership functions and sparsity-promoting constraints to encourage concise rules. Evaluations on clinical EHR datasets show that EvolveFNN attains predictive performance comparable to standard RNNs while producing compact rule sets interpretable to clinicians. The paper emphasizes rule-extraction fidelity, ablation of temporal vs. static modules, and qualitative clinical validation of inferred rules. Limitations include sensitivity to EHR heterogeneity and the need for multi-site validation; the authors recommend augmenting the pipeline with multimodal data (text, images), uncertainty quantification for rule confidence, and transfer strategies to reduce site bias for real-world deployment.

B. CTGAN + Tree-based pipeline for early lung-cancer detection (2024)

This study addresses sample scarcity and class imbalance in tabular lung-cancer screening datasets by employing a Conditional Tabular GAN (CTGAN) to synthesize minority- class examples and combining those with classical tree- based classifiers (notably Random Forest and XGBoost).

The workflow: (1) preprocess clinical and tabular imaging- derived features, (2) train CTGAN to generate realistic conditional samples, (3) evaluate multiple classifiers with and without synthetic augmentation under cross-validation, and (4) compare against traditional oversampling methods such as SMOTE. Results demonstrate substantial performance gains after CTGAN augmentation, with tree ensembles delivering stable, high-accuracy decisions. Key methodological insights include calibration checks for synthetic sample distribution, ablation between generative and non-generative augmentation, and systematic metric reporting (precision, recall, F1). Future work proposed includes multimodal extension to imaging + tabular fusion, formal privacy and distribution-shift audits for generated data, and prospective validation on multi-center cohorts before clinical translation.

C. VAE-driven multimodal fusion for cardiac disease detection (2024)

This work develops a VAE-centric fusion pipeline that encodes chest X-ray imagery and structured clinical data into a shared latent space for downstream cardiac condition classification. Convolutional backbones with attention modules (e.g., EfficientNet variants with channel/spatial attention) extract image embeddings, while tabular/structured features are processed via transformer- style encoders; both modalities are projected into a VAE latent distribution and concatenated for classification. The VAE acts as a regularized fusion mechanism that encourages modality-aligned representations and robust generalization. Experiments on a large cardiac dataset indicate that VAE fusion surpasses unimodal baselines and conventional concatenation strategies, particularly for under-represented conditions when combined with resampling. The authors advocate further exploration of richer latent priors, multimodal pretraining, federated learning for privacy, and external validation across institutions to confirm generalizability.

D. Dysarthria detection via deep speech representation learning (2024)

Focusing on Parkinson's-related dysarthria, this paper constructs a sizeable task-diverse speech corpus and applies deep representation learning to raw audio, replacing handcrafted acoustic features. The pipeline trains or fine- tunes self-supervised speech encoders and attaches lightweight classifiers for dysarthria detection across tasks (sustained vowels, read sentences, free speech). The learned representations yield strong discriminative performance and more robust cross-task transfer than MFCC-based baselines. Analyses include sensitivity to recording length, per-task contribution, and demographic subgroup performance. Limitations include disease-specificity and dataset scope, motivating future extensions to multi-cause dysarthria datasets, severity regression (not only binary classification), longitudinal monitoring for progression, and integration with remote-care platforms for telemedicine.

E. Handwriting kinematics for Alzheimer's detection (2024)

This study applies ensemble machine-learning to fine- grained tablet-recorded handwriting kinematics for discriminating Alzheimer's disease from healthy controls. The pipeline emphasizes careful preprocessing (outlier handling, normalization), feature engineering on temporal- spatial dynamics, per-model feature selection (ANOVA/RFE), and a stacking ensemble to combine complementary classifiers. Cross-validation and Monte- Carlo experiments demonstrate high AUC and robustness to sampling variation, indicating handwriting micro-motor signatures carry early cognitive decline signals. The work identifies major limitations: relatively small cohort sizes and need for longitudinal studies to capture prodromal (MCI) progression.

Suggested future directions include multimodal fusion with cognitive tests and neuroimaging, larger and more diverse cohorts, and deployment studies for low-cost screening in community-health settings.

F. Synthesis and open directions

Across these works, two clear trajectories emerge: (1) interpretability vs. performance trade-offs — interpretable fuzzy/RNN hybrids and ensemble approaches strive to keep clinician trust while achieving high accuracy; (2) data scarcity & distributional robustness — generative augmentation (CTGAN, VAE) and multimodal fusion are common strategies to mitigate imbalance and boost generalization. For future research, we recommend: standardized external validation protocols, formal uncertainty and calibration assessment for models trained on synthetic data, federated or privacy-preserving training for multi-site studies, and clinically-oriented interpretability studies that quantify how model explanations affect decision-making. Integrating these concerns will increase the likelihood of safe, equitable translation of early- detection AI systems into practice.

III. COMPARATIVE ANALYSIS OF EXISTING APPROACHES

Algorithm / Family	Typical Use in Healthcare Forecasting	Data Type & Best Suitability	Compute / Deployment
LSTM (Long Short-Term Memory)	Multi-step time- series forecasting (ECG, vitals)	Sequential numeric signals; moderate–long horizons	Moderate– high (GPU recommended for large datasets); edge feasible with model compression
GRU (Gated Recurrent Unit)	Same as LSTM but lightweight	Sequential signals where latency matters	Lower compute than LSTM; good for mobile/embed ded
Transformer & Variants (e.g., TFT, TransEHR)	Long-range, multi- horizon forecasting; multi-modal fusion	Long time-series, asynchronous EHR events, multivariate signals	High (large GPU/TPU); recent efficient variants reduce cost
CNN / Conv- LSTM hybrids	Feature extraction from raw waveforms (ECG) and short-term pattern detection	Raw signals, images (ultrasound), spectrograms	Moderate; CNNs are parallelizable
Random Forest (RF)	Tabular risk classification (CKD, diabetes risk)	Structured clinical/lab features, aggregated time-window stats	Low– moderate; easy to deploy
XGBoost / LightGBM	High-accuracy tabular predictions & risk scoring	Structured features, aggregated time- window metrics	Low– moderate; production- ready
ARIMA / SARIMA (Statistical)	Baseline time-series forecasting for vitals (stable trends)	Univariate numeric series with stationarity/season ality	Low; CPU-only
Autoencoders / VAE (Anomaly Detection)	Unsupervised anomaly detection in vitals/ECG	Raw signals or feature vectors	Moderate; depends on network size
SVM (Support Vector Machine)	Binary/multi-class risk classification on engineered features	Small–medium tabular datasets	Low– moderate; CPU feasible
Ensemble methods (stacking RF/XGBoost + LSTM/Transfor mer)	Combine tabular + temporal models for robust forecasting/classific ation	Multi-source data (tabular + sequences)	High (multiple models), but can be optimized for deployment

Table 1: Comparative Analysis of Existing Approaches

IV. RESEARCH GAP

Despite significant advancements in AI-driven healthcare analytics, several critical research gaps remain in the domain of predictive forecasting for early health risk detection.

A. Limited Focus on Predictive Forecasting

Most existing healthcare systems concentrate on real-time monitoring or threshold-based alert generation rather than true future risk forecasting. While many studies detect abnormalities after they occur, only a limited number of works focus on predicting health deterioration hours or days in advance, which restricts proactive medical intervention.

B. Insufficient Long-Term Temporal Modeling

Several traditional machine learning approaches rely on static or short-window features extracted from medical data. These models fail to capture long-term temporal dependencies and evolving trends in physiological signals such as ECG, blood pressure, and glucose levels, leading to reduced forecasting accuracy for chronic and progressive diseases.

C. Lack of Multi-Modal Data Integration

Existing research often analyzes single data sources (e.g., only ECG or only laboratory results). There is a noticeable lack of frameworks that effectively integrate multiple health signals, including vitals, historical medical records, and demographic information, to generate comprehensive and personalized risk predictions.

D. Limited Explainability in Deep Learning Models

Although deep learning models such as LSTM and Transformer demonstrate high predictive accuracy, many existing systems lack explainable AI mechanisms. This creates a “black-box” effect, reducing clinical trust and limiting real-world adoption by healthcare professionals who require transparent and interpretable decision support.

E. Inadequate Handling of Imbalanced Medical Data

Medical datasets often contain highly imbalanced classes, with fewer critical events compared to normal cases. Many existing studies do not adequately address this imbalance, leading to biased models with high accuracy but poor sensitivity for rare yet life-threatening conditions.

F. Lack of External Validation and Generalization

A significant portion of prior research evaluates models on a single dataset or limited patient cohort. The absence of external validation across different hospitals or populations raises concerns about model generalization and real-world applicability.

G. High Computational Complexity and Deployment Challenges

State-of-the-art models, especially Transformer-based architectures, require high computational resources, making them difficult to deploy in resource-constrained healthcare settings. Efficient, scalable, and lightweight forecasting models remain underexplored.

H. Limited Integration with Clinical Decision Support Systems

Many existing predictive models operate independently without seamless integration into clinical workflows. There is a gap in developing systems that provide actionable insights, risk scores, and recommendations that can be directly used by clinicians for decision-making. Current research lacks a unified, explainable, and scalable AI-based forecasting framework that can accurately predict early health risks using long-term temporal patterns and multi-modal medical data. Addressing these gaps is essential to move from reactive monitoring toward truly preventive and intelligent healthcare systems.

V. SYSTEM ARCHITECTURE AND METHODOLOGY

A. System Architecture

The proposed smart healthcare system architecture is designed to support predictive forecasting and early risk detection through AI-driven analysis of medical data. The architecture follows a modular and layered approach to ensure scalability, interpretability, and efficient model deployment.

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1) Data Source Layer

This layer consists of heterogeneous healthcare data sources, including electronic health records (EHRs), clinical laboratory reports, historical vital sign measurements (blood pressure, glucose levels, heart rate), and biomedical signals such as ECG. These data sources provide both structured and time-series information required for predictive modeling.

2) Data Preprocessing Layer

Raw healthcare data often contains noise, missing values, and inconsistencies. This layer performs data cleaning, normalization, missing-value imputation, noise filtering (especially for ECG signals), and time-series segmentation. Feature scaling and data balancing techniques are also applied to improve model stability and performance.

3) Feature Engineering and Representation Layer

In this layer, meaningful features are extracted from preprocessed data. These include statistical features (mean, variance, standard deviation), temporal features (trends, moving averages), and domain-specific features such as heart rate variability and ECG morphological patterns. For deep learning models, raw sequences or transformed representations are directly fed into the network to preserve temporal dependencies.

4) AI Prediction Layer

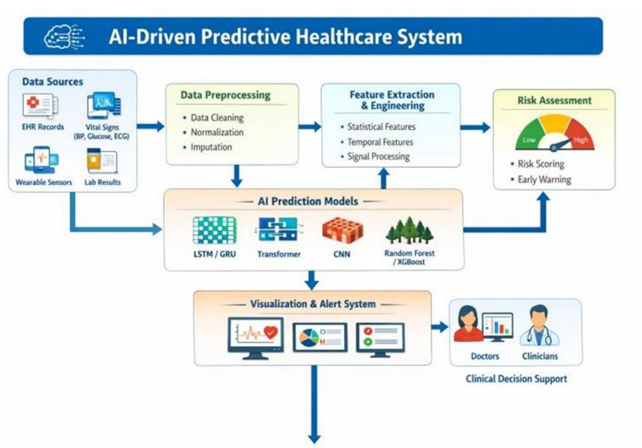
This is the core intelligence layer of the system. Advanced machine learning and deep learning models such as LSTM, GRU, CNN, Transformer, Random Forest, and XGBoost are employed to learn temporal patterns and relationships in patient data. Sequence models forecast future health indicators, while classification models estimate the probability of health risk events.

5) Risk Assessment and Decision Layer

Based on model outputs, a risk scoring mechanism categorizes patients into low, medium, or high-risk groups. Thresholds and probabilistic confidence scores are used to support early detection of potential health deterioration and enable timely clinical intervention.

6) Visualization and Alert Layer

This layer presents predictive results through dashboards and visual analytics. Time-series plots, risk scores, and alert notifications are generated to assist healthcare professionals in understanding patient conditions and making informed decisions.



B. Methodology

The methodology adopted in this research follows a systematic workflow to ensure accurate and reliable predictive healthcare forecasting.

1) Step 1: Data Collection

Healthcare datasets are collected from publicly available medical repositories and clinical records. The datasets include time-series vitals, ECG signals, laboratory values, and patient demographic information.

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2) Step 2: Data Preprocessing

Data cleaning techniques are applied to handle missing values, outliers, and noise. Normalization and standardization are performed to ensure uniform feature scales. For time- series data, windowing and segmentation techniques are used to prepare input sequences.

3) Step 3: Feature Extraction and Selection

Relevant temporal and statistical features are extracted to represent patient health status effectively. Feature selection techniques are applied to reduce redundancy and improve model generalization.

4) Step 4: Model Development and Training

Multiple AI models are trained and evaluated, including traditional machine learning classifiers and deep learning forecasting models. Hyperparameter tuning and cross- validation are performed to enhance predictive accuracy.

5) Step 5: Predictive Forecasting

The trained models are used to forecast future health indicators and identify early signs of potential medical risks. Multi-step forecasting enables prediction over extended time horizons.

6) Step 6: Risk Classification and Evaluation

Predicted outputs are converted into risk categories using probabilistic thresholds. Model performance is evaluated using metrics such as accuracy, precision, recall, F1-score, RMSE, and AUC-ROC.

7) Step 7: Interpretation and Visualization

Explainable AI techniques and visual analytics are used to interpret model predictions and present results in an understandable manner for clinical use.

The proposed system architecture and methodology provide a comprehensive AI-driven framework for predictive forecasting in healthcare. By combining advanced deep learning models with structured data processing and risk assessment mechanisms, the system enables early detection of health risks and supports proactive, data-driven medical decision-making.

VI. MATHEMATICAL MODEL

The proposed system is designed to predict early health risks by analyzing historical patient health data using Artificial Intelligence–based forecasting models.

1) System Definition

Let the system be defined as:

S={I,P,F,M,O}S = \{I, P, F, M, O\}S={I,P,F,M,O}

Where:

I = Input data

P = Preprocessing functions

F = Feature extraction

M = Prediction models

O = Output (Risk prediction)

2) Input (I)

Let the patient health dataset be: I={x1,x2,x3,...,xn}

Where each xix_ixi represents a health parameter such as: Blood Pressure (BP)

Blood Sugar (Glucose) Heart Rate (HR)

ECG signals

Kidney indicators (Creatinine, Urea)

Each patient record over time is represented as:

X_t=[BP_t ,$Sugar_t$,HR_t,ECG_t,$Kidney_t$]X_t = [BP_t, Sugar_t, HR_t, ECG_t, Kidney_t]X_t=[BP_t,$Sugar_t$,HR_t,ECG_t,$Kidney_t$]

3) Preprocessing (P)

Preprocessing removes noise and prepares the data:

$P(X)=Normalize(X)+Missing\ Value\ Imputation$

Normalized value:

$X'=\sigma X-\mu$

Where:

μ = mean

σ = standard deviation

4) Feature Extraction (F)

Extract temporal and statistical features:

F={mean,variance,trend,time_dependency}

For time-series window www:

$Ft=f(Xt-w,...,Xt)$

5) Prediction Model (M)

a) LSTM / GRU Model

Given a sequence of inputs:

$$X=X1,X2,...,XT$$

The model predicts future health state:

$$Y^t+k=M(X1:t)$$

Where:

k = prediction horizon (24–48 hours)

Y^ = predicted risk score

6) Output (O)

O={Risk Level, Probability, Alert}

Example outputs:

High BP risk detected

Possible kidney failure risk

Early cardiac risk warning

7) Objective Function

The model minimizes prediction error:

$$Loss=n1i=1\sum n(Yi-Y^i)2$$

For classification:

$$\mathrm{Loss}=-\sum \mathrm{Ylog(Y\hat{})}$$

8) Final Outcome

The system predicts future health risks before symptoms become critical, enabling early medical intervention and preventive healthcare.

VII. PROPOSED MODEL

The proposed model focuses on AI-based predictive forecasting for early risk detection in smart healthcare systems. Unlike conventional healthcare monitoring systems that only report current patient conditions or generate alerts after abnormal values occur, the proposed approach emphasizes anticipatory healthcare, where future health risks are predicted in advance.

The system leverages time-series medical data, including vital signs (blood pressure, heart rate, blood glucose), biomedical signals (ECG), and historical clinical records. These data are processed and analyzed using advanced deep learning models such as Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and Transformer-based architectures, which are well-suited for modeling temporal dependencies and long-term trends in physiological data.

At a high level, the model consists of four main components:

1) Data Preparation Module: Medical time-series data is cleaned, normalized, and segmented into meaningful sequences. Noise reduction techniques are applied, especially for ECG and continuous vitals, to improve signal quality.
2) Forecasting Engine: Sequence learning models such as LSTM and Transformer networks are trained to forecast future health indicators over a defined prediction horizon (e.g., 24–48 hours). These models learn temporal patterns that may indicate gradual health deterioration.
3) Risk Scoring Mechanism: Forecasted outputs are transformed into a risk score representing the probability of a potential health event (e.g., cardiac risk, kidney failure risk). Based on predefined thresholds, patients are categorized into low, medium, or high-risk groups.
4) Decision Support Layer: The final outputs include predictive alerts, trend visualizations, and interpretable risk indicators to support proactive clinical decision-making.

By integrating AI-based forecasting with risk assessment, the proposed model aims to shift healthcare systems from reactive treatment to preventive and personalized care, thereby improving patient outcomes and reducing emergency interventions.

VIII. DISCUSSION

Predictive forecasting using AI has the potential to significantly transform healthcare delivery. By identifying early warning signs before critical events occur, clinicians can initiate timely interventions, adjust treatment plans, and reduce hospital admissions.

One of the major advantages of forecasting-based healthcare systems is their ability to analyze trends rather than isolated readings. For instance, a gradual rise in blood pressure or creatinine levels over time may not trigger immediate alerts in traditional systems, but predictive models can recognize such trends as early indicators of cardiovascular or kidney-related risks.

However, several challenges must be addressed for effective implementation. Data quality and availability remain critical concerns, as medical datasets often contain missing values, noise, and inconsistencies. Additionally, class imbalance—where critical events are rare compared to normal cases—can negatively affect model performance if not handled properly.

Another challenge is model interpretability. While deep learning models offer high accuracy, their black-box nature can limit trust among healthcare professionals.

Incorporating explainable AI techniques is essential to ensure clinical acceptance.

From an accuracy perspective, forecasting models such as LSTM and Transformers have demonstrated superior performance in capturing long-term temporal dependencies compared to traditional machine learning approaches.

However, computational complexity and resource requirements may limit real-time deployment in low- resource healthcare environments.

Overall, despite these challenges, predictive healthcare systems offer a promising path toward proactive, data- driven, and patient-centric medical care.

IX. CONCLUSION

This study highlights the growing importance of predictive forecasting for early risk detection in smart healthcare systems using AI. Traditional healthcare monitoring approaches are limited by their reactive nature, often identifying medical conditions only after symptoms become severe. By leveraging advanced AI models such as LSTM, GRU, and Transformer architectures, predictive healthcare systems can analyze historical and time-series medical data to forecast future health risks. This proactive approach enables early intervention, improves clinical decision-making, and supports personalized healthcare delivery.

Although challenges related to data quality, interpretability, and deployment remain, continued research and advancements in AI techniques can address these limitations. Predictive healthcare systems represent a critical step toward **preventive medicine**, improved patient outcomes, and more efficient healthcare systems.

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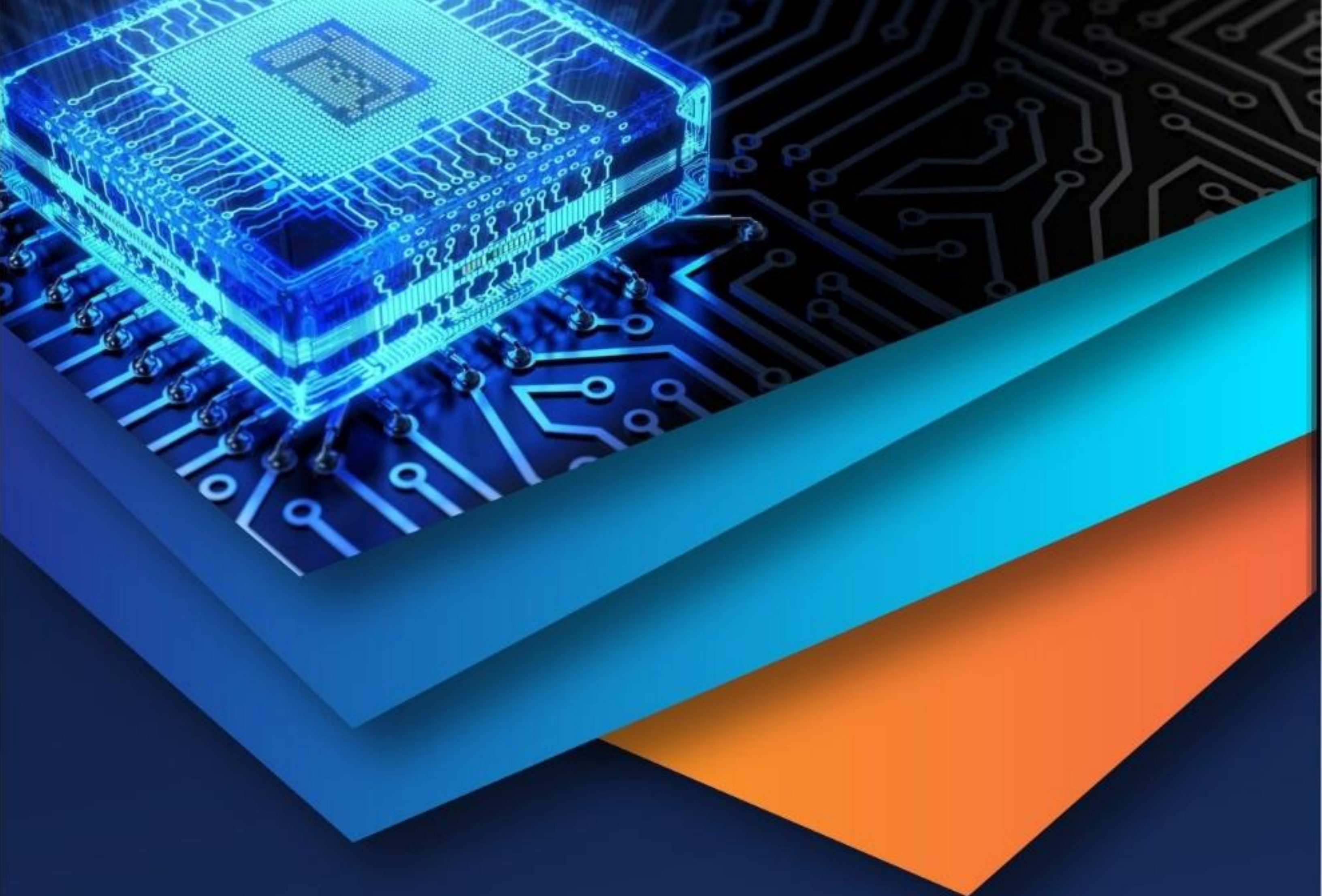

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