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Aranya AI

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Abstract: Limited access to veterinary services in rural areas often delays livestock disease detection and results in economic losses for farmers. To address this issue, this paper presents Aranya-AI, an artificial intelligence-based livestock health monitoring and management system designed for early disease detection and improved animal welfare. The system utilizes a Convolutional Neural Network (CNN) for image-based disease identification and an LSTM Autoencoder for anomaly detection in physiological time-series data. These models are integrated through a conversational chatbot interface that provides automated health insights and preventive recommendations in an accessible manner. Additionally, the cloud-based architecture ensures secure and scalable data handling. Experimental evaluation demonstrates improved diagnostic accuracy and system responsiveness, supporting timely decision-making in rural farming environments. The proposed system contributes toward sustainable and technology-enabled livestock management.
Keywords: Livestock Health Monitoring, Artificial Intelligence, CNN, LSTM Autoencoder, EWMA, RAG, Chatbot, Precision Livestock Farming, Smart Farmer.

I. INTRODUCTION

The agricultural sector produces large volumes of data related to livestock health, productivity, and environmental conditions. Effective utilization of such data is necessary for maintaining animal well-being and improving farm efficiency. However, farmers in rural regions often experience limited access to veterinary professionals, making continuous monitoring and early disease detection difficult.

Traditional livestock management primarily depends on manual observation followed by delayed medical intervention. As reported in prior studies, delayed diagnosis significantly increases disease spread and mortality rates [1], [5]. Smallholder farmers usually lack technological tools to monitor physiological parameters such as temperature, appetite, heart rate, and activity levels in real time. Consequently, preventable illnesses may remain unnoticed until they become severe.

Another challenge involves the absence of timely diagnostic guidance. Farmers frequently rely on traditional practices or must travel long distances to consult veterinarians. Accurate disease identification based on visible symptoms typically requires expert knowledge, which is not always available. Furthermore, fragmented data storage practices limit long-term analysis and raise security concerns. Artificial intelligence has recently shown promise in precision livestock farming by enabling automated disease detection and predictive analytics [6], [7]. Deep learning models, particularly CNNs, have demonstrated strong performance in detecting infectious cattle diseases from images [12], [3]. Similarly, AI-driven monitoring platforms have been explored for improving livestock healthcare outcomes [9]. Motivated by these developments, this paper proposes **Aranya-AI**, an intelligent livestock health monitoring system that integrates CNN-based image classification [12], LSTM-based anomaly detection, and a chatbot-driven advisory interface within a secure cloud environment.

The primary objective is to enhance early disease detection, improve accessibility to diagnostic support, and ensure secure livestock data management. The remainder of this paper is organized as follows: Section II reviews related work, Section III presents the methodology, Section IV discusses results, and Section V concludes the study with future directions.

II. LITERATURE REVIEW

A. Livestock Health Monitoring Systems

Recent monitoring platforms employ IoT sensors, cloud computing, and mobile applications to track animal health indicators. Systems such as Cowlar and Nexus Smart Livestock provide real-time alerts and behavioral insights [1]. However, these solutions are largely oriented toward commercial farms and may not be economically viable for smaller operations. Many existing platforms focus either on sensor analytics or image-based diagnosis, leading to incomplete health assessments. Research suggests that multimodal AI systems can significantly improve diagnostic reliability [8]. Additionally, dependence on stable internet connectivity restricts adoption in rural settings. These observations highlight the need for a unified and accessible monitoring system capable of combining multiple diagnostic approaches.

B. Data Security in Agricultural Systems

As agriculture becomes increasingly digitized, protecting sensitive data has emerged as an important concern. Cloud-based platforms remain vulnerable to unauthorized access if strong safeguards are not implemented [4].

Common practices include encryption, role-based access control, and secure authentication. Nevertheless, several livestock platforms still rely on basic protection mechanisms, which may not sufficiently safeguard farmer data. Establishing secure architectures is therefore essential for improving user trust and adoption.

C. Research Gap and Motivation:

Table I compares existing livestock monitoring systems with the proposed Aranya-AI platform. While current solutions provide basic monitoring capabilities, they lack comprehensive AI integration, strong data security, and user-friendly advisory support for small-scale farmers. Most systems do not combine image-based disease detection, time-series anomaly analysis, and conversational interfaces within a single platform.

To address these limitations, Aranya-AI integrates CNN-based image classification, LSTM-based anomaly detection, and a chatbot interface with secure cloud storage. This integrated approach aims to improve early disease detection, accessibility, and data security, making it more suitable for rural and resource-constrained farming environments.

Table I: Comparison of Livestock Health Monitoring Systems

System	Key Features	Accessibiliy	Security Level	AI Integration
Cowlar	IoT-based health tracking, real-time alerts	Moderate	Standard	Partial (ML-based)
AgriSense	Environmental monitoring, sensor-based data collection	Limited (rural)	Basic	None
Nexus Smart Livestock	GPS tracking, temperature, and activity monitoring	Moderate	High	Partial
Aranya-AI *(Proposed)*	LSTM+CNN hybrid model, chatbot integration, secure cloud storage	High	Advanced (AES + RBAC)	Full (AI-driven)

This comparison highlights that while existing systems offer basic health monitoring capabilities, they often lack comprehensive AI integration, robust security, and accessibility for small-scale farmers

III. METHODOLOGY

This section describes the architecture and implementation of Aranya-AI, an AI-driven livestock health monitoring system designed for early disease detection and farmer-centric decision support. The system integrates time-series analysis, image-based disease detection, and conversational AI within a secure and scalable framework.

A. System Architecture:

Aranya-AI follows a three-layer architecture consisting of a presentation layer, application layer, and data layer, as illustrated in Fig. 1. The presentation layer provides a web-based interface that allows farmers to interact with the chatbot, upload livestock images, and view health insights. The application layer manages system logic and integrates AI models, including an LSTM Autoencoder for anomaly detection in physiological data and a CNN for image-based disease classification. The data layer handles secure storage of livestock records and AI predictions using a MongoDB database.

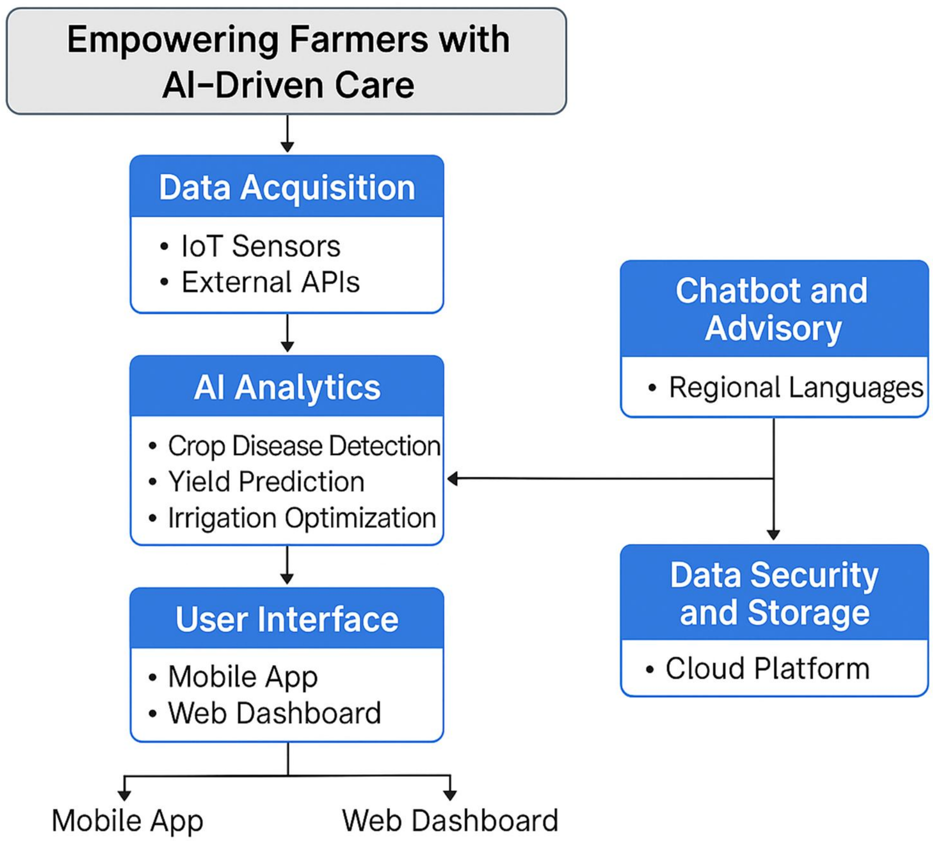

Fig. 1. Architecture and workflow of the proposed Aranya-AI system.

B. Mathematical Model: LSTM Autoencoder for Anomaly Detection

Based on the implementation in the AranyaAI notebook, the system utilizes an LSTM Autoencoder to detect anomalies in cattle health metrics.

1) Model Architecture

The model is designed to learn temporal patterns associated with healthy livestock behavior. It consists of two components:

- Encoder: Compresses input sequences into a latent representation.
- Decoder: Reconstructs the sequence from the latent vector.

The input is defined as:

$$X = \{x_1, x_2, \ldots, x_T\}$$

where $T = 24$and $x_t \in \mathbb{R}^d$, with $d = 4$features: temperature, activity level, appetite, and heart rate.

2) Mathematical Formulation

Encoder:

$$h_t = LSTM_{enc}(x_t, h_{t-1}), z = h_T$$

The encoder contains 128 units with ReLU activation.

Latent Representation:

$$Z_{seq} = \{z, z, ..., z\}$$

Decoder:

$$\hat{h}_t = LSTM_{dec}(z, \hat{h}_{t-1})$$

Reconstruction:

$$\hat{x}_t = W\hat{h}_t + b$$

3) Training Objective

The model is trained in an unsupervised manner using healthy cattle data. The objective is to minimize reconstruction error through Mean Absolute Error (MAE):

$$L_{MAE} = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{1}{Td}\sum_{t=1}^{T}\sum_{j=1}^{d} | x_{t,j}^{(i)} - \hat{x}_{t,j}^{(i)} |\right)$$

The Adam optimizer is applied for gradient descent.

4) Anomaly Detection Algorithm

After training, normal sequences produce low reconstruction error.

1. Error Calculation:

$$E = mean(| X_{new} - \hat{X}_{new} |)$$

2. Threshold Selection:

The anomaly threshold $\tau$is determined using the 95th percentile of validation errors.

Classification:

- Healthy if $E \leq \tau$
- Anomalous if $E > \tau$

This approach enables early identification of abnormal health patterns before visible symptoms appear.

C. Chatbot Module

The chatbot serves as the primary farmer-facing interface and operates in two distinct modes, illustrated in Fig. 4:

Aranya Mode: General livestock advisory powered by a configurable primary LLM (with automatic fallback to a secondary provider if unavailable). The chatbot uses the farmer's animal profile for personalized context. When the model detects that web search would improve the answer (signaled by a [SEARCH_NEEDED:] tag in the response), it triggers a DuckDuckGo search with Wikipedia and curated veterinary source fallbacks, then uses the retrieved context for an augmented response.

Chiron Intelligence Mode: A RAG-based advisory system that queries a Pinecone vector database of ingested veterinary manuals and clinical guidelines. Retrieved documents are injected into the LLM context along with the specific animal's health profile. Responses cite knowledge base sources, minimizing hallucination and providing evidence-based recommendations.

Both modes use Server-Sent Events (SSE) for real-time token-by-token streaming with live thinking indicators, ensuring sub-300ms first-token latency and a responsive experience even on slower rural connections.

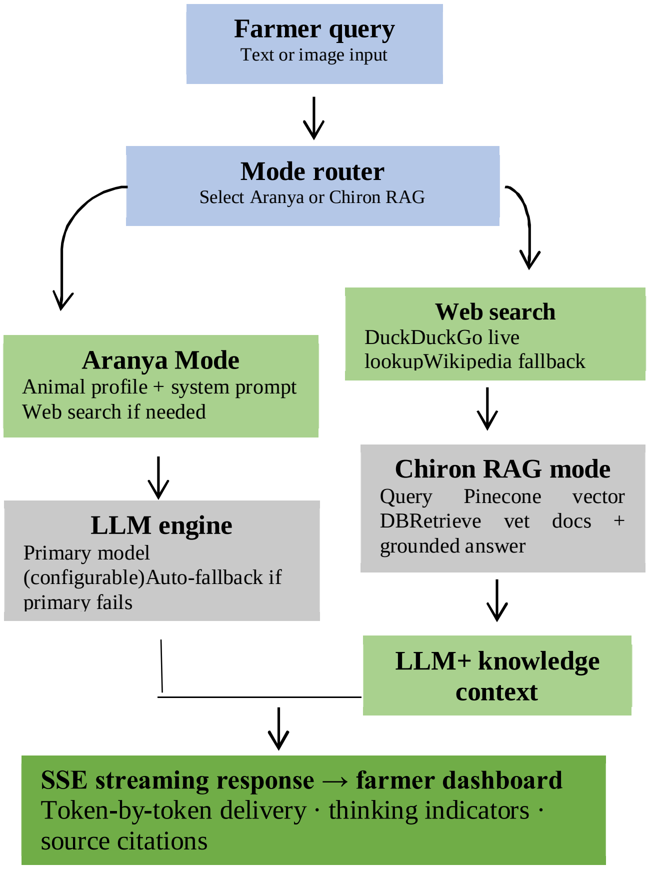

Figure 2. Dual- mode chatbot architecture- Aranya Mode (web- augumented advisory) and Chiron Intelligence Mode (RAG- grounded responses).

D. Security Design

To ensure data confidentiality and integrity, Aranya-AI incorporates multiple security mechanisms across all layers. Secure communication is enforced using HTTPS with SSL/TLS encryption, while sensitive data is encrypted at rest using AES-256. Role-Based Access Control (RBAC) restricts data access based on user roles, and audit logs are maintained to track system activities. These measures ensure ethical data handling and build trust among users.

E. Implementation Details

The system is implemented using Python and JavaScript. The frontend is developed using React.js, while the backend is built with Node.js and Express. AI models are deployed using Flask-based RESTful APIs. MongoDB is used for scalable cloud data storage, and deep learning models are implemented using TensorFlow, Keras, and Hugging Face Transformers.

IV. RESULT AND DISCUSSION

A. Model Performance Analysis

The performance of Aranya-AI was evaluated using two primary components: the CNN-based disease classification model and the LSTM Autoencoder for anomaly detection in physiological data.

The CNN model was trained on labeled livestock disease images covering multiple categories, including skin infections, ocular conditions, and mobility-related disorders. The model achieved an average classification accuracy of 92%, which represents an improvement over baseline CNN architectures that typically report accuracies near 85% in similar agricultural datasets [2].

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In addition to overall accuracy, precision and recall values remained consistently high across disease classes, suggesting balanced model behavior with minimal bias toward dominant categories. This consistency is important in livestock healthcare scenarios, where missed detections can lead to delayed treatment.

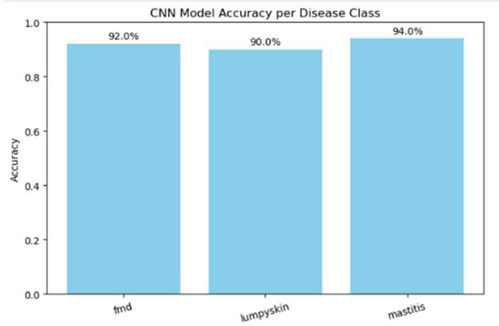

Figure 3. CNN model accuracy per livestock disease class.

The LSTM Autoencoder was evaluated using time-series cattle health metrics, including body temperature, activity level, appetite, and heart rate. The model achieved an anomaly detection accuracy of **89%**, demonstrating its capability to distinguish normal physiological patterns from abnormal ones.

Reconstruction error analysis showed that healthy behavioral sequences produced consistently low error values, whereas anomalous conditions generated noticeable spikes. This behavior confirms the model's ability to detect early physiological deviations before visible symptoms appear, thereby supporting preventive livestock care.

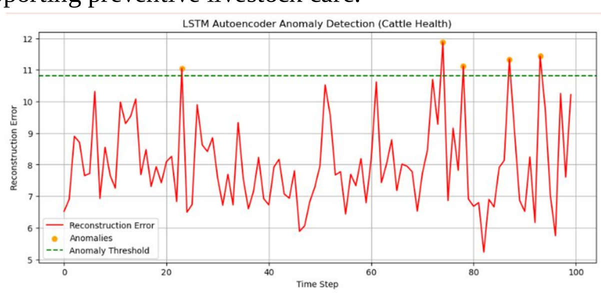

Fig.4 – LSTM Autoencoder Anomaly Detection

The training behavior of the LSTM Autoencoder was further examined by monitoring Mean Absolute Error (MAE) across epochs. Both training and validation losses decreased steadily, indicating stable learning and effective convergence. Moreover, the relatively small gap between the curves suggests minimal overfitting and acceptable generalization performance on unseen data.

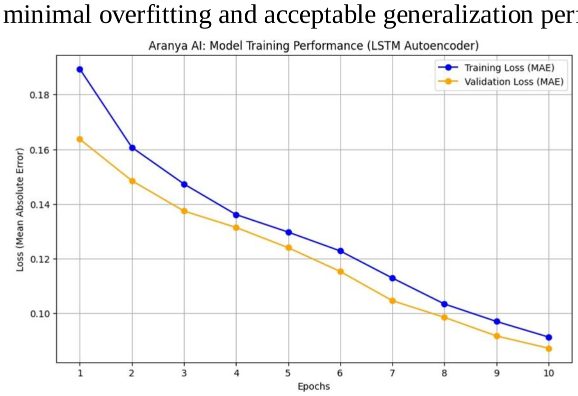

Fig.5 – Training and validation loss curves of the LSTM Autoencoder.

B. Comparative Accuracy Analysis

To further validate the proposed approach, the performance of the developed CNN model was compared with a baseline architecture.

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TABLE II: COMPARARATIVE ANALYSIS OF METHOD ACCURACIES

Model	Accuracy
Baseline CNN	85%
Proposed CNN	92%
LSTM Autoencoder	89%
Vital Range Fallback Classifier (< 10 logs)	Score-based (0–10 severity scale)
EWMA MLEngineeredMonitor	Multi-species rule engine (5-point persistence)

C. System Efficiency and Response Time

System responsiveness plays an essential role in real-world agricultural deployments. Latency was therefore measured across major system components.

- CNN prediction time: approximately 450 ms
- LSTM anomaly detection time: approximately 380 ms
- Chatbot response time: below 300 ms

These results indicate that the system supports near real-time interaction without noticeable delay. During testing, multiple concurrent requests were handled without significant performance degradation, suggesting that the modular Node.js–Flask architecture scales reasonably well.

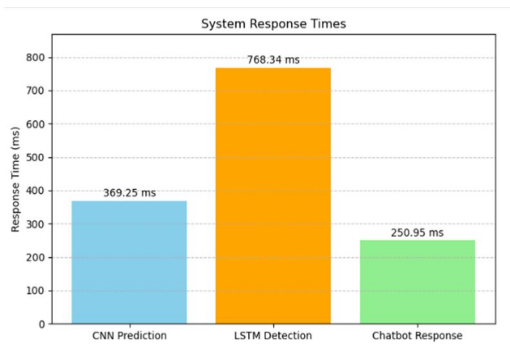

Fig.6 – System Response Times

D. Chatbot Evaluation

The chatbot was evaluated based on response relevance, usability, and interpretability of AI-generated recommendations. It effectively translated technical outputs into actionable guidance, such as recommending veterinary consultation when abnormal health patterns were detected.

Preliminary user testing involving a small participant group indicated that farmers found the interface relatively intuitive after brief exposure. Multilingual capability further improved accessibility, particularly for users more comfortable with regional languages.

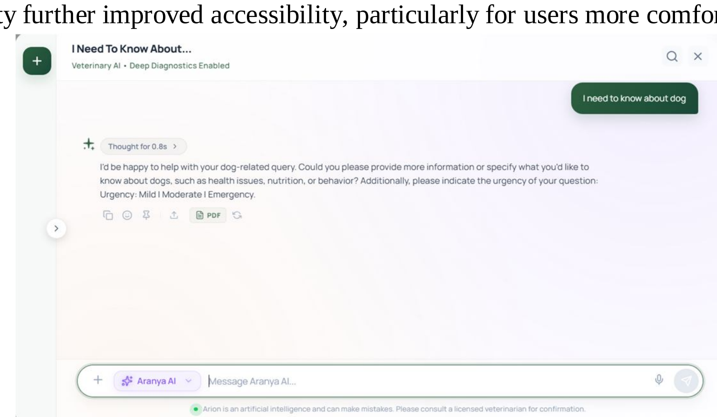

Fig.7 – Aranya-AI Mode interface showing farmer interaction

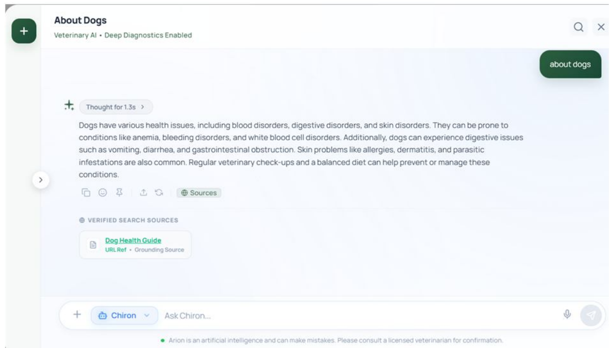

Fig.7.1-Chiron Mode chatbot interface showing farmer interaction

E. Scalability and Deployment Observations

The cloud-backed MongoDB infrastructure enabled reliable storage and retrieval of livestock records. Load testing suggested that the system can support expansion to larger farming networks with minor infrastructure modifications.

However, performance may depend on network availability. In regions with limited connectivity, asynchronous data synchronization or offline buffering mechanisms may be required to ensure smoother operation.

F. Comparative Discussion

Compared to existing livestock monitoring platforms such as Cowlar and AgriSense, which primarily emphasize sensor-based tracking, Aranya-AI offers a more integrated diagnostic framework by combining image analytics, time-series anomaly detection, and conversational AI.

This multimodal approach aligns with recent research highlighting the advantages of AI-driven precision agriculture [6], [8]. Furthermore, the inclusion of secure communication protocols enhances system reliability relative to platforms with limited security implementation [4].

G. Limitations

Despite encouraging results, several limitations should be acknowledged:

The dataset included partially synthetic data.

User evaluation was conducted on a relatively small scale.

Rural connectivity constraints may influence system responsiveness.

Future validation using large-scale real-world datasets is necessary to further establish system robustness.

H. Practical Implications

The findings suggest that Aranya-AI can support earlier disease detection, reduce livestock mortality, and enable more informed veterinary decisions while improving overall farm productivity. The system appears particularly beneficial for smallholder farmers who may lack immediate access to professional healthcare services.

V. CONCLUSION

This research presented Aranya-AI, an intelligent livestock health monitoring system designed to support farmers through early disease detection, secure data management, and accessible AI-driven insights. The system integrates

CNN-based image disease classification, LSTM Autoencoder-based anomaly detection, and a chatbot interface to provide proactive livestock healthcare support. Experimental evaluation demonstrated that Aranya-AI can effectively identify visible livestock diseases and detect abnormal health patterns from physiological data, enabling timely intervention in rural and resource-limited environments. The secure architecture, supported by encryption and role-based access control, ensures data privacy while maintaining system reliability and scalability.

The proposed system highlights the potential of combining artificial intelligence and digital agriculture to improve animal welfare, reduce economic losses, and enhance farm sustainability. By offering a farmer-centric and modular design, Aranya-AI provides a strong foundation for future smart livestock management solutions.

Future work will focus on integrating IoT-based real-time sensing, expanding multilingual chatbot support, and validating system performance through large-scale field deployment to further enhance practical applicability.

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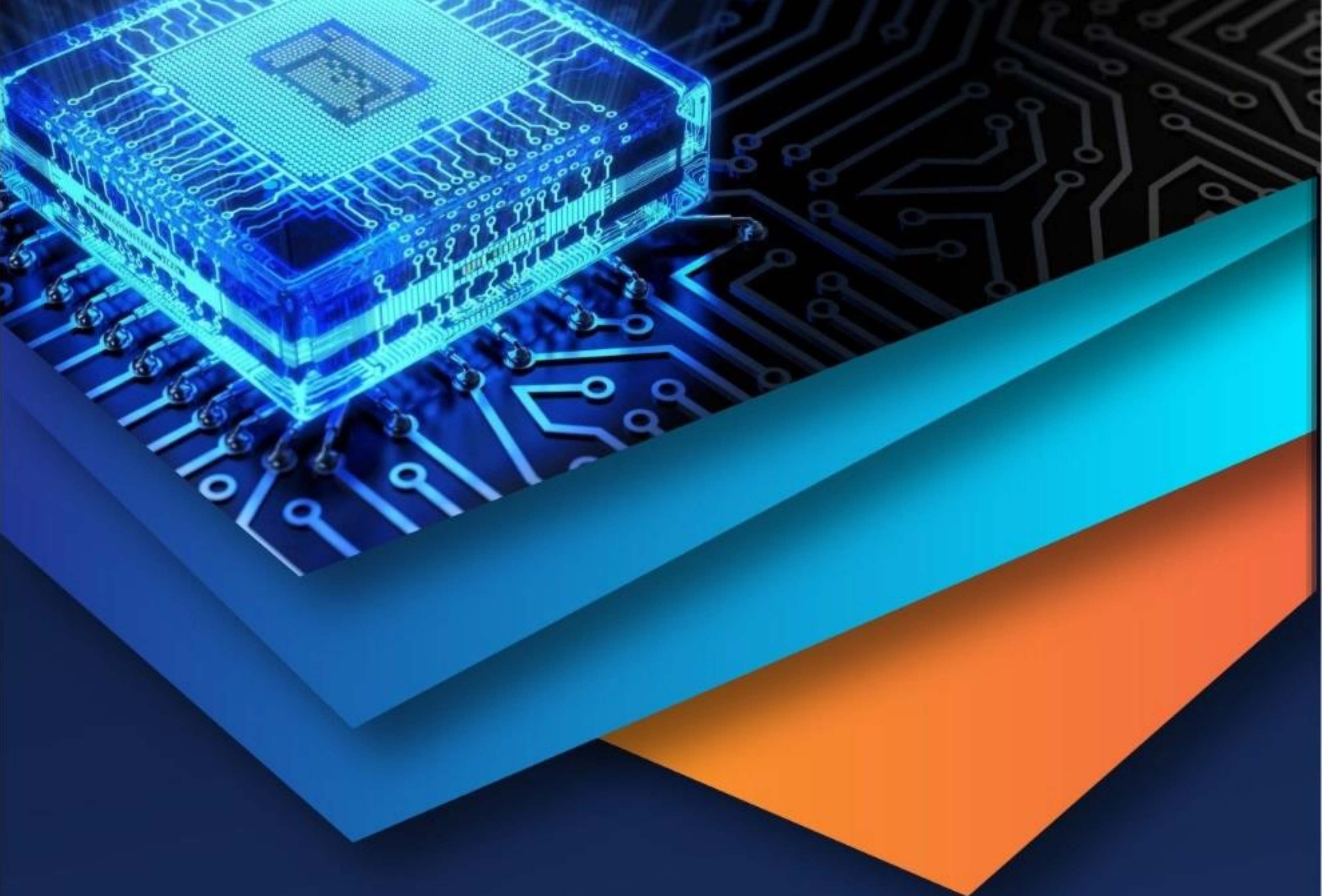

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