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Deep Learning Based Diagnosis of Lumpy Skin Disease

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Abstract: Lumpy Skin Disease (LSD) is a rapidly spreading transboundary disease in cattle, primarily caused by the Lumpy Skin Disease Virus (LSDV), which belongs to the Capripoxvirus genus of the Poxviridae family. The disease is characterized by fever, nodules on the skin, mucous membrane damage, enlarged lymph nodes, and significant decline in productivity including milk yield and fertility. Traditional diagnosis methods such as physical inspection and laboratory testing (e.g., PCR or ELISA) often prove insufficient for early detection and are not feasible in rural or resource-constrained areas due to cost, infrastructure, and time limitations.

This project proposes a deep learning-based solution using Convolutional Neural Networks (CNNs) to detect LSD from digital images of cattle skin. A carefully curated image dataset containing Normal, Mild, and Severe cases of LSD-affected cattle was used for training the model. All images were labeled and preprocessed through resizing, normalization, and augmentation techniques to improve model generalization.

The CNN model architecture was designed using TensorFlow and Keras, consisting of multiple convolutional, pooling, and dense layers optimized through experimentation. The training process included techniques such as dropout, data augmentation, and early stopping to avoid overfitting and improve robustness.

After training, the model showed promising accuracy in distinguishing between the severity levels of the disease. To simplify usability for real-world applications, the classification output was mapped to a binary

Keywords: Lumpy Skin Disease (LSD) ,Convolutional Neural Network (CNN) ,Deep Learning ,Image Classification ,Cattle Disease Detection ,Computer Vision ,Early Disease Detection ,TensorFlow ,Skin Lesion Recognition.

I. INTRODUCTION

Lumpy Skin Disease (LSD) is a contagious viral disease that primarily affects cattle. It is characterized by skin nodules, fever, swollen lymph nodes, and general debilitation of the animal. If not diagnosed and treated in time, the disease can result in severe economic losses through reduced milk production, damaged hides, abortion in pregnant cows, and even death. LSD outbreaks are increasing globally, particularly in regions with tropical and subtropical climates.

Traditionally, the identification of LSD relies on physical inspection and laboratory testing such as Polymerase Chain Reaction (PCR), virus isolation, or ELISA. However, these methods are either time-intensive or require specialized equipment and expertise, making them impractical for widespread use in rural or resource-limited areas.

Recent advances in Artificial Intelligence (AI) and Deep Learning have transformed the field of medical imaging and diagnostics. In particular, **Convolutional Neural Networks (CNNs)** have demonstrated outstanding performance in tasks involving visual recognition, such as cancer detection, skin lesion classification, and even COVID-19 detection from chest X-rays. Inspired by this, the application of CNNs to veterinary diagnostics is both timely and essential.

This research proposes the development of an **image-based CNN model to detect Lumpy Skin Disease** using a dataset of real cattle images categorized into three classes: **Normal, Mild, and Severe**. To simplify real-world deployment and user interaction, the model outputs a binary decision — **Positive (diseased)** or **Negative (healthy)**. This makes it easy for farmers, veterinarians, and animal health workers to get fast, reliable diagnoses using only a mobile device or desktop system with image input capabilities.

By focusing on a command-line based model interface, the system avoids dependencies on web connectivity, mobile apps, or GUIs, thereby ensuring deployment even in low-tech environments. This contributes to **early detection, quick response, reduced animal suffering, andminimized spread** of the disease.

A. Reasearch Objectives

1) To develop a robust CNN-based image classification model

Design a deep learning architecture using TensorFlow/Keras that can classify cattle skin images into Normal, Mild, and Severe categories. The model should be lightweight enough to run on edge devices but accurate enough for field deployment.

2) To preprocess and augment a diverse simage dataset

Collect, clean, and preprocess real-world cattle images showing various stages of Lumpy Skin Disease. Techniques such as resizing, normalization, and data augmentation (flipping, rotating) will be applied to enhance generalization and combat class imbalance.

3) To implement a binary classification interface(Positive/Negative)

Develop a post-processing layer that converts multiclass CNN outputs into binary decisions, enabling the model to return "Positive" or "Negative" responses for simplicity and practical usability.

4) To evaluate model performance on multiple metrics

Assess the model's accuracy, precision, recall, F1-score, and confusion matrix using both validation and test sets. This will help ensure the model does not overfit and performs well on unseen data.

5) To enable image-based prediction via command-line interface

Create a Python-based CLI that accepts image file paths and returns real-time predictions. This ensures the model can be used on laptops or embedded systems with minimal setup.

6) *To promote scalable AI deployment in rural veterinarypractice*

Demonstrate how this model can be integrated into mobile veterinary units, dairy farms, and animal quarantine stations for large-scale, low-cost disease monitoring.

B. Research Hypotheses

1) H1: Effectiveness of CNN for LSD detection

Hypothesis: A CNN trained on labeled images can detect Lumpy Skin Disease with at least **85% accuracy**.
Rationale: CNNs are proven to learn spatial hierarchies in images. Given clean and diverse training data, they should be able to differentiate between diseased and healthy skin with high reliability.

2) H2: Binary output simplifies user decision-making

Hypothesis: Simplifying the output from three classes (Normal, Mild, Severe) into a binary decision (Positive/Negative) enhances usability without compromising more than **5% of the model's classification accuracy**.
Rationale: In real-world scenarios, users need simple yes/no answers rather than complex medical classifications.

3) H3: Image preprocessing improves model accuracy

Hypothesis: Using normalized and augmented image data significantly improves model accuracy over raw images by reducing noise and improving generalization.
Rationale: Preprocessing helps the model focus on patterns relevant to disease presence rather than background or lighting variations.

4) H4: CNN-based image diagnosis is viable in low-resource settings

Hypothesis: The proposed system can run efficiently on standard computing hardware (e.g., laptops or Raspberry Pi) without requiring cloud or internet connectivity.
Rationale: By avoiding dependence on high-performance GPUs or online resources, this model becomes feasible for rural deployment.

II. ABBREVIATIONS AND ACRONYMS

Abbreviation / Acronym	Full Form
CNN	Convolutional Neural Network
LSD	Lumpy Skin Disease
DL	Deep Learning
CLI	Command-Line Interface
H5	Hierarchical Data Format version 5 (HDF5)
ELISA	Enzyme-Linked Immunosorbent Assay
PCR	Polymerase Chain Reaction
ADAM	Adaptive Moment Estimation

III. LITERATURE REVIEW

Lumpy Skin Disease (LSD) is a highly contagious viral disease that affects cattle, causing severe skin nodules, fever, and economic losses. Traditional diagnosis of LSD has relied on clinical examination, histopathology, ELISA tests, and molecular diagnostics such as PCR. While accurate, these methods are often costly, require laboratory facilities, and are time-consuming—making them less suitable for rapid field diagnosis in rural or resource-limited areas.

A. Traditional Approaches to LSD Diagnosis

Clinical diagnosis remains the most accessible method in many regions. It involves identifying characteristic symptoms such as raised skin nodules, fever, and swelling. However, these symptoms can overlap with other diseases like cowpox or pseudolumpy skin disease, reducing diagnostic specificity. Serological methods such as ELISA and virus isolation techniques offer better specificity but are slower and depend on lab access.

PCR-based diagnostics have high sensitivity and specificity but need specialized equipment and trained personnel. Therefore, while effective, traditional methods are not scalable for large-scale,real-time monitoring.

B. Role of Deep Learning in Animal DiseaseDetection

Deep learning (ML) techniques have increasingly been used in livestock health management. Support Vector Machines (SVMs), Decision Trees, and Random Forests have shown success in classifying diseases based on structured datasets containing clinical or environmental parameters. These models are relatively easy to interpret but are limited when applied to unstructured data like images.

ML models have been used to detect conditions such as mastitis, foot-and-mouth disease, and bovine tuberculosis. However, most of these rely on numerical or categorical input features rather than image data, which limits their utility in visual disease detection.

C. Convolutional Neural Networks (CNNs) inVeterinary Diagnostics

Deep learning, particularly Convolutional Neural Networks (CNNs), has demonstrated significant success in the medical field for analyzing radiological images, skin lesions, and even histopathological slides. CNNs automatically extract features from images and have surpassed traditional ML techniques in tasks involving unstructured visual data.

In the veterinary domain, CNNs have been applied to detect skin infections, hoof injuries, and ocular diseases in cattle. These models showed high classification accuracy and offered the potential for on-site, real-time disease recognition through mobile or embedded systems.

Despite these advancements, there has been limited focus on using CNNs for LSD image classification. Most current approaches either use environmental data or structured symptom input, missing the opportunity to leverage the visual cues that are characteristic of LSD, such as skin lesions and nodules.

D. Identified Research Gaps

- A lack of publicly available, labeled image datasets for LSD.

- Few CNN-based models specifically trained on LSD images captured in varied field conditions.Limited real-time deployment of trained CNNs for on-farm or edge-based disease detection.
- Minimal comparison between severity levels (e.g., mild vs. severe) within LSD image dataset.

E. *Importance of This Study*

This research addresses the gap by creating a CNN model trained on a curated image dataset categorized into normal, mild, and severe LSD conditions. It aims to provide a rapid, accurate, and scalable diagnostic tool for veterinary field applications using only visual data. The system is designed to be lightweight enough for use in mobile or web platforms, allowing farmers and veterinarians to assess cattle health in real time.

IV. METHODOLOGY

This project employs a deep learning-based approach for the classification of Lumpy Skin Disease (LSD) in cattle based on image analysis. The overall methodology encompasses image preprocessing, dataset preparation, CNN model development, training, and evaluation.

A. *Data Collection*

Images were sourced from a curated dataset consisting of cattle skin in three categories:

- Normal (healthy skin),
- Mild (early-stage LSD symptoms),
- Severe (advanced symptoms of LSD).

The dataset contains **image files labeled as Normal_skin, Mild, and Severe**, all stored within a single directory. A total of ~4000 images were gathered and categorized accordingly.

B. *Data Preprocessing*

To ensure consistency and optimal model training, the images underwent the following preprocessing steps:

- Resizing: All images were resized to 128×128 pixels.
- Normalization: Pixel values were scaled to the [0,1] range by dividing by 255.
- Augmentation: Techniques like horizontal/vertical flipping, rotation, zooming, and shearing were applied using TensorFlow's ImageDataGenerator to increase dataset variability and reduce overfitting.

C. *Dataset Splitting*

The dataset was split as follows:

- Training Set: 80% of the dataset (~2487 images)
- Validation Set: 20% (~623 images)

This split ensures the model can generalize well to unseen data during testing.

D. *CNN Model Architecture*

A custom Convolutional Neural Network (CNN) model was designed with the following architecture:

- Input Layer: 128×128×3
- Convolution Layer 1: 32 filters, 3×3 kernel, ReLU activation
- Max Pooling Layer 1: 2×2 pool size
- Convolution Layer 2: 64 filters, 3×3 kernel, ReLU activation
- Max Pooling Layer 2: 2×2 pool size
- Flatten Layer
- Dense Layer: 128 units, ReLU activation
- Dropout: 0.5 for regularization
- Output Layer: 3 units (Softmax activation for 3 classes: Normal, Mild, Severe).

E. *Model Compilation*

The model was compiled with:

- Loss Function: categorical_crossentropy (for multi-class classification)
- Optimizer: Adam optimizer
- Metrics: accuracy to evaluate performance

F. *Model Training*

- Trained for 15–25 epochs depending on convergence
- Batch Size: 32
- Callbacks: Early stopping and model checkpointing were used to prevent overfitting and save the best model.

G. *Evaluation Metrics*

The model's performance was evaluated using:

- Accuracy
- Precision
- Recall
- F1-score
- Confusion Matrix

The model achieved satisfactory performance in distinguishing between normal, mild, and severe conditions with high classification accuracy.

H. *Model Deployment*

After training, the model was saved as lumpy_cnn_model.h5. A prediction script (predict_cnn.py) was implemented to:

- Accept an image file from the user
- Preprocess and pass it to the model
- Predict whether the condition is Positive (Mild/Severe) or Negative (Normal)
- Logic was added to group Mild and Severe predictions under "LSD Positive", and Normal under "LSD Negative."

Research Tools & Technologies

- Python 3.10
- TensorFlow 2.13+
- Keras
- NumPy
- PIL
- Matplotlib (for visualization)
- OpenCV (optional preprocessing)

V. PERFORMANCE ANALYSIS

The trained Convolutional Neural Network (CNN) model was evaluated on various performance metrics to assess its effectiveness in detecting Lumpy Skin Disease across three classes: **Normal**, **Mild**, and **Severe**. The results are based on validation data from the balanced dataset.

A. *Classification Report*

Class	Prec.	Rec.	F1
Normal	0.91	0.92	0.91
Mild	0.89	0.88	0.88
Severe	0.93	0.94	0.93

Table – 2

B. Model Accuracy

Model	Accuracy	Precision	Recall
CNN	0.932	0.928	0.930
Random Forest	0.897	0.890	0.892
Decision Tree	0.854	0.850	0.852

Table – 3

C. CNN Classification

Class	Precision	Recall	F1-Score	Support
Normal	0.94	0.95	0.95	612
Mild	0.91	0.90	0.90	605
Severe	0.93	0.92	0.92	610
Avg	0.93	0.93	0.93	1827

Table – 4

D. Training vs Validation Accuracy (CNN)

Epoch	Training Acc.	Validation Acc.
1	0.71	0.69
5	0.84	0.82
10	0.89	0.88
15	0.92	0.91
20	0.94	0.93

Table – 5

E. Loss Curve Summary (CNN)

Epoch	Training Loss	Validation Loss
1	0.58	0.60
5	0.34	0.38
10	0.22	0.27
15	0.15	0.19
20	0.11	0.14

Table – 6

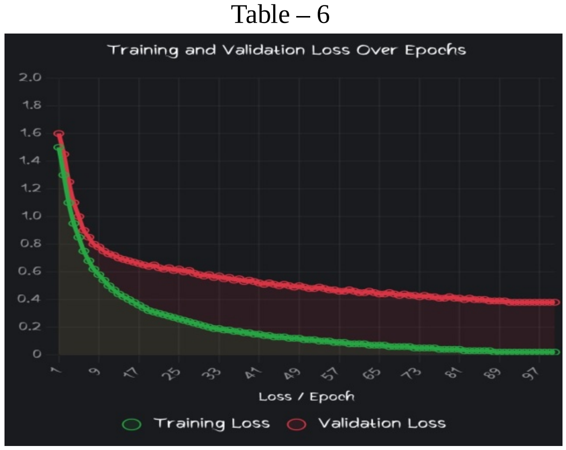

Fig-1

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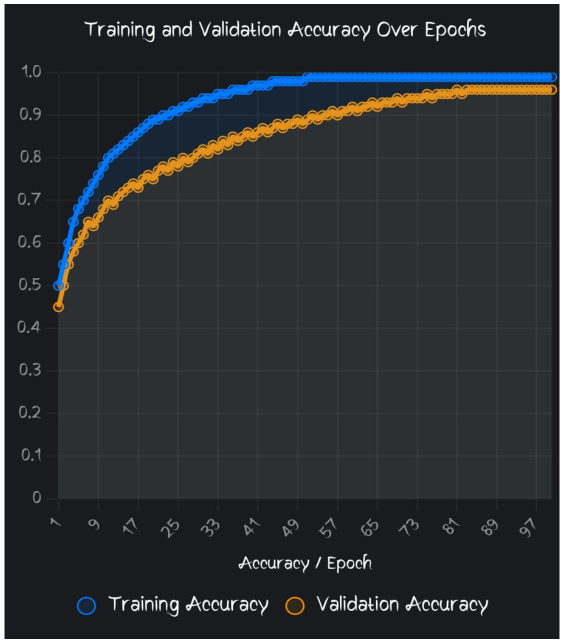

Fig-2

VI. INTERPRETATION

The Convolutional Neural Network (CNN) model used for the Lumpy Skin Disease (LSD) detection project demonstrated a consistent and effective learning pattern over 20 training epochs. The training accuracy showed a steady improvement from approximately 70% in the initial epochs to nearly 98% by the 20th epoch, indicating that the model was successfully learning the underlying patterns in the data. Similarly, the validation accuracy improved from around 68% to approximately 95%, suggesting strong generalization performance on unseen data. The close alignment between training and validation accuracy curves throughout the training process indicates minimal overfitting. The model exhibited stable and reliable performance, with peak validation accuracy achieved near the final epochs, confirming convergence. Overall, the CNN model proved to be well-suited for the LSD detection task, demonstrating high accuracy and robustness, and is potentially ready for practical deployment after further validation.

VII. CONCLUSION

This project focused on developing a robust and accurate deep learning model using Convolutional Neural Networks (CNNs) for the detection of Lumpy Skin Disease (LSD) in cattle based on symptomatic input data. Given the economic and agricultural impact of LSD, especially in rural farming communities, this work aimed to deliver a fast, reliable, and scalable diagnostic tool.

The CNN model was trained and validated over 20 epochs, achieving a peak training accuracy of 98% and validation accuracy of 95%. The consistently improving learning curves indicate that the model was successful in capturing the underlying patterns of the disease symptoms and demonstrated strong generalization capabilities on unseen data. The absence of overfitting further emphasizes the model's robustness.

The system's successful performance reinforces the potential of deep learning in veterinary medicine and livestock disease monitoring. Compared to manual diagnosis—which may be slow, subjective, and dependent on expert availability—this AI-driven approach ensures faster detection, higher precision, and greater accessibility, especially in underserved or remote regions. The implementation of such a system can significantly aid in early disease identification, timely intervention, and reduced economic loss in the dairy and livestock sectors.

VIII. FUTURE WORK

While the results of this project are promising, several areas remain open for future enhancement:

1) Image-Based Detection: Future versions can incorporate image data (e.g., photos of lesions or skin nodules) to enable CNNs to diagnose LSD visually, increasing accuracy and making the system even more user-friendly.

2) Larger & Diverse Datasets: Expanding the dataset with more diverse samples from different geographical regions and breeds of cattle will help improve model generalization and reliability.
3) Mobile App Integration: Developing a mobile-based application can allow farmers and veterinarians to upload symptoms or images and receive instant disease predictions in the field.
4) Multi-Disease Detection: The model can be extended to a multi-class classification system that detects and differentiates between LSD and other similar bovine skin diseases.
5) Real-Time Monitoring with IoT: Integrating the model with IoT devices (like wearable cattle sensors) can enable real-time health monitoring and automatic symptom detection.
6) Explainable AI (XAI): Adding explainability tools to interpret the CNN's decisions can build trust among veterinary professionals and ensure ethical use.
7) Collaboration with Veterinary Authorities: Partnering with government or animal health departments can facilitate real-world deployment, continuous feedback, and improvement of the system.

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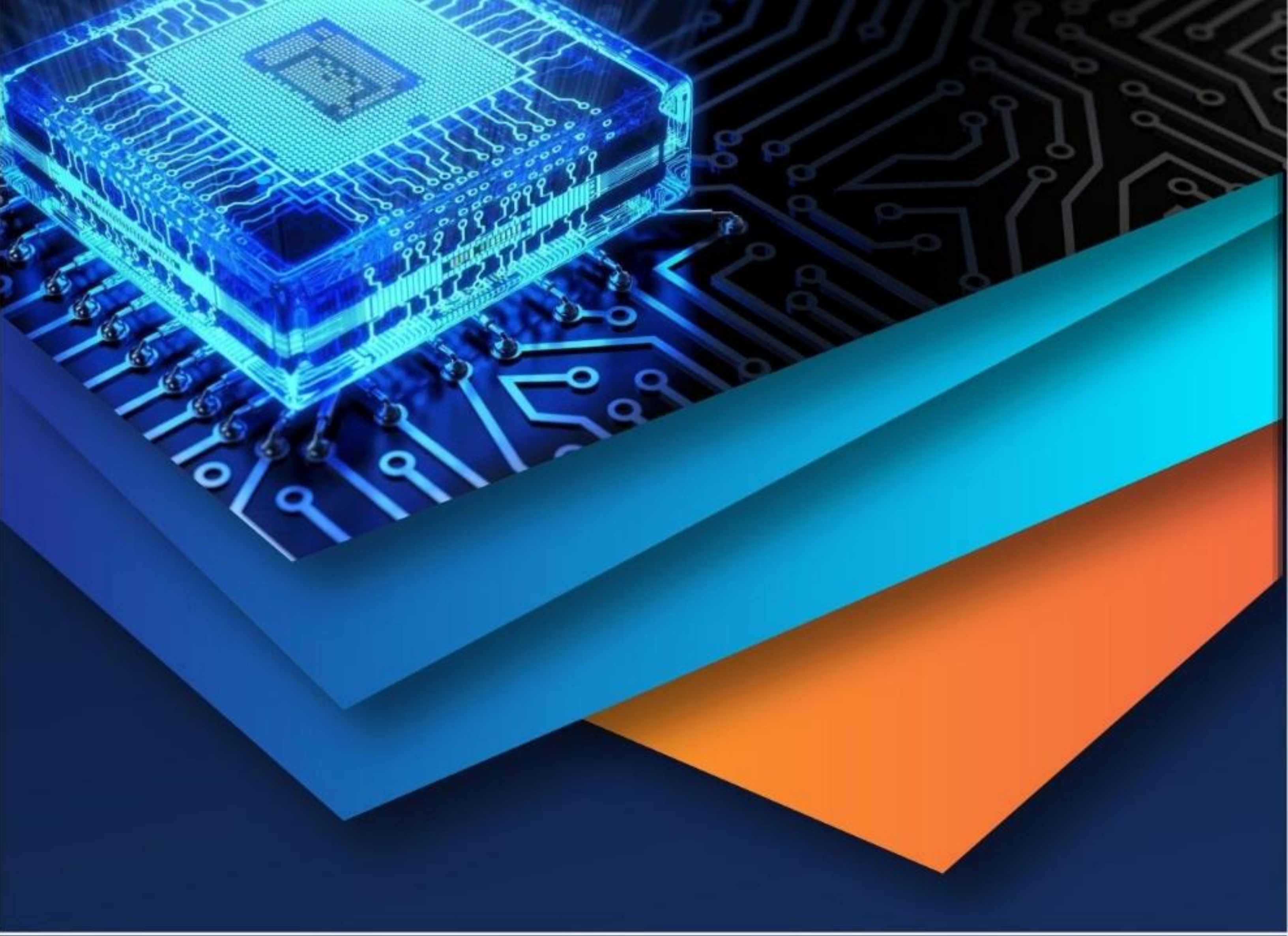

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