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An Approach for Wild Animal Detection in Videos by using Deep Learning

Padmapriya J[1], B. Dileep[2], CH. Anupriya[3], V. Sowmiya[4]
[1]Assistant Professor, [2, 3, 4]B-Tech Student, Vidya Jyothi Institute of Technology, Hyderabad, Telangana, India

Abstract: Due to land availability decreases and rapid urbanisation many wild animals near the forest areas comes out for water and food. Wild animal detection strives to address the critical issue of manual surveillance challenges faced by forest officers and conservationists in vast natural habitats. Traditional methods, such as periodic surveys and camera traps, have proven inadequate in providing real-time data and comprehensive coverage, impeding effective conservation efforts. Moreover, budget constraints and the absence of automation further exacerbate these challenges. In response, our project proposes an innovative solution that seamlessly integrates deep learning and instant messaging technologies, fostering affordable and continuous surveillance. By harnessing edge computing and freely available messaging channels, our system aims to significantly enhance real-time visibility and data-driven decision-making in conservation. The primary goal is to empower conservationists with timely and actionable information for informed decision-making. Through the deployment of advanced deep learning algorithms, our system can recognize and track wildlife activity, triggering instant notifications to forest officers and relevant stakeholders via instant messaging platforms.

Keywords: Alerting system, Deep learning, Surveillance,

I. INTRODUCTION

In the heart of our planet's vast and biodiverse natural habitats, a critical challenge persists-one that demands innovative solutions to protect our environment and preserve biodiversity. Forest officers and conservationists have long grappled with the limitations of traditional manual surveillance methods, such as periodic surveys and camera traps. These methods, while valuable, have proven inadequate in providing real-time data and comprehensive coverage, hindering the effectiveness of conservation efforts. Budget constraints and the absence of automation further compound these challenges, creating a pressing need for a transformative approach. In response to this urgent need, the proposed wild animal detection model sets out to revolutionize wildlife monitoring and conservation practices. It recognizes that the power of modern technology can be harnessed to bridge the gap between traditional conservation methods and the demands of our rapidly changing world. By integrating deep learning and instant messaging technologies, this innovative solution aims to provide affordable and continuous surveillance in even the most remote natural habitats. Through the deployment of advanced deep learning algorithms, this system possesses the remarkable capability to recognize and track wildlife activity, facilitating the instantaneous transmission of notifications to forest officers and relevant stakeholders via widely accessible instant messaging platforms. This real-time approach is poised to not only enhance the efficacy of conservation efforts but also mitigate the looming risks of habitat degradation and illegal activities, underscoring our unwavering commitment to biodiversity preservation.

II. PROBLEM DEFINITION

The Wildlife Detection System addresses the challenges of traditional manual surveillance in natural habitats, which often face limitations such as the infrequency of surveys, delayed data from camera traps, budget constraints, and a lack of automation. These obstacles hinder effective conservation efforts, leading to habitat degradation and the rise of illegal activities. By integrating deep learning and instant messaging technologies, this project aims to improve real-time monitoring, provide timely information, and bridge the gap between conventional methods and modern technological solutions. Ultimately, the goal is to support ecosystem preservation and enhance wildlife conservation efforts.

The primary objective of this system is to enhance wildlife monitoring by combining deep learning algorithms with instant messaging tools. This integration is designed to address common issues associated with manual surveillance, including delayed data, limited coverage, and budget limitations. With advanced deep learning, the system can detect and track wildlife activity in real time, sending instant alerts to relevant stakeholders. This not only strengthens decision-making in conservation but also helps prevent habitat destruction and combat illegal activities, reinforcing the commitment to preserving biodiversity and protecting natural heritage.

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A user-friendly interface will enable forest officers to receive immediate notifications and access real-time surveillance data on wildlife activity. To ensure the system's accuracy, reliability, and effectiveness, field tests and validation studies will be conducted across various natural habitats. The system will also be designed with an emphasis on affordability, scalability, and sustainability, ensuring it is accessible and usable for conservationists and forest officers over the long term.

III. LITERATURE SURVEY

Wild animal detection research aims to tackle the critical challenges of manual surveillance faced by forest officers and conservationists in large, remote natural habitats. Traditional methods, such as periodic surveys and camera traps, are often inadequate for providing real-time data and comprehensive coverage, which hampers effective conservation efforts. Additionally, budget constraints and the lack of automation further complicate these challenges.

In response, this research proposes an innovative solution that integrates deep learning with instant messaging technologies to enable affordable, continuous surveillance. By leveraging edge computing and freely available messaging platforms, the proposed system seeks to greatly enhance real-time monitoring and data-driven decision-making, thereby improving the effectiveness of wildlife conservation efforts.

Meenakshi et al. [5], in their work discussed a system that combined YOLOv4 and LoRa to identify the presence of wild animals and notify the appropriate wildlife authority. The prediction of the intrusion of wild animals uses a hybrid model for the prediction of the system. The work involves evaluating the performance of various algorithms, comparing their accuracies, and ultimately identifying the most efficient one for the task.

Patil et al. [6], established a computerized device that detects the invasion of wild animals and attracts them back into the forest without doing any harm, the proposed system aims to protect people and livestock at the periphery of the forest area/fields, thereby minimizing the risk of injury triggered by the Human-Wildlife dispute. Simulating triggering events and environmental outcomes, such as a wild animal entering the area of interest, is straightforward.

Nikhil et al. [7], suggested an approach that explains how combining the Internet of Things and Machine Learning methods can make irrigation smarter. The proposed approach helps farmers grow suitable crops based on soil parameters by using Machine Learning techniques. The approach helps the farmers avoid issues by having ongoing surveillance over the field, and it also aids in preventing attackers like wild animals from entering the field. Additionally, it promotes water conservation by automatically providing plants and fields with the least quantity of water necessary in accordance with their needs.

Panda et al. [8], detected intrusions employing ultrasonic sensors at the corners of the field. Subsequently, a camera installed on an electric vehicle, equipped with a Node microchip microcontroller, captures photographs of the intruder to aid in field surveillance. The farmer is then alerted through an IoT application. The effectiveness of the proposed system has been evaluated based on the acquired photographs of the intruder and the notification alert. The provided model enables efficient identification of any type of encroachment around the field.

Giordano et al. [9] also proposed a system for detecting intrusions in agricultural lands. In the agriculture industry, the adoption of the Internet of Things has enabled smart farming and precision agriculture, among others. It is described in this article how Internet of Things software has been developed for crop security to prevent animals from entering agricultural fields. Agricultural systems can be protected from possible damage from wild animal assaults and meteorological conditions by employing repelling and monitoring equipment.

IV. METHODOLOGY

Deep learning, a subset of artificial intelligence, enables systems to learn from large datasets and make decisions without explicit programming. In the context of wild animal detection, deep learning algorithms are trained to recognize patterns in images or videos, identifying and classifying animals based on their features. By utilizing convolutional neural networks (CNNs) and other deep learning architectures, these systems can analyse visual data from camera traps, drones, or satellite imagery with high accuracy and efficiency.

The integration of deep learning into wildlife detection systems has the potential to revolutionize conservation practices by enabling real-time monitoring, reducing human intervention, and improving data accuracy. It can help researchers gather valuable insights on animal behaviour, migration patterns, and habitat use, contributing to more informed conservation strategies and better protection of endangered species.

A. Video Capture

The user must log in to access the video. The methodology discussed will capture the video, then localize the objects in the video frame. Each frame of the video is given as input to the classification module which returns the class name of that object detected and the respective count of that object will be recorded and updated in the database.

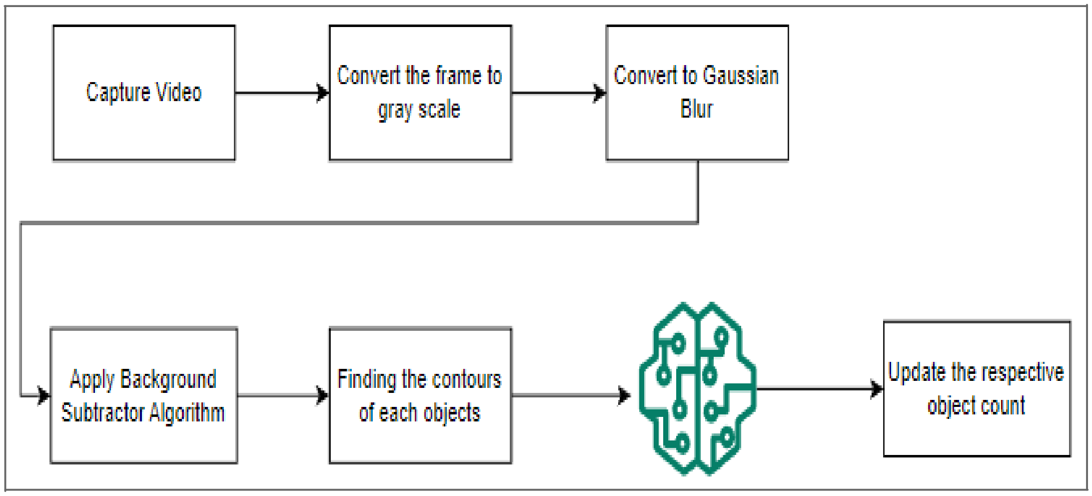

Fig. 1 workflow of video capture

B. Classification Model

The classification model is used to group the given objects into their respective classes. Further, it takes the image-frame of the video as input and it classifies the object by using the trained model of different wild animal images. The classification of wild animal images in a video involves several stages: extracting frames, detecting animals, classifying them using deep learning models, tracking their movements across frames, and analysing the data for further insights. This process aids in conservation, biodiversity monitoring, and environmental research, providing an efficient and automated method for studying wildlife in their natural habitats.

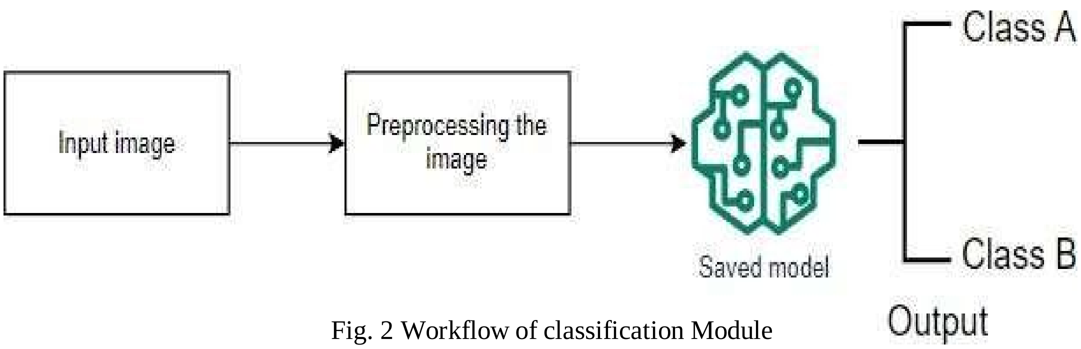

Fig. 2 Workflow of classification Module

C. Overall Workflow

The overall workflow of the method is divided into two parts: model training and real- time object counting. In model training, the video frames are pre-processed and trained with a deep learning algorithm that is integrated with a camera. In real time object counting, the images are captured and the algorithm is applied to the images so that different classes of wild animal are identified.

In object detection, the target object classification and localization are performed simultaneously where the target class has been categorized and separated from the background by drawing bounding boxes (BBs) on input images containing the entire object. This can be particularly useful for counting endangered species for accurate surveying.

The experiment is performed an extensive and elaborate study to explore the comparative performance analysis of the proposed YOLO models for endangered wildlife classification and object localization. From the initial custom endangered wildlife species dataset consisting of 1600 images has been further expanded tenfold by utilizing various data augmentation procedures (i.e., colour balancing, rotation, blur processing, mirror projection, brightness transformation) to obtain a correct result.

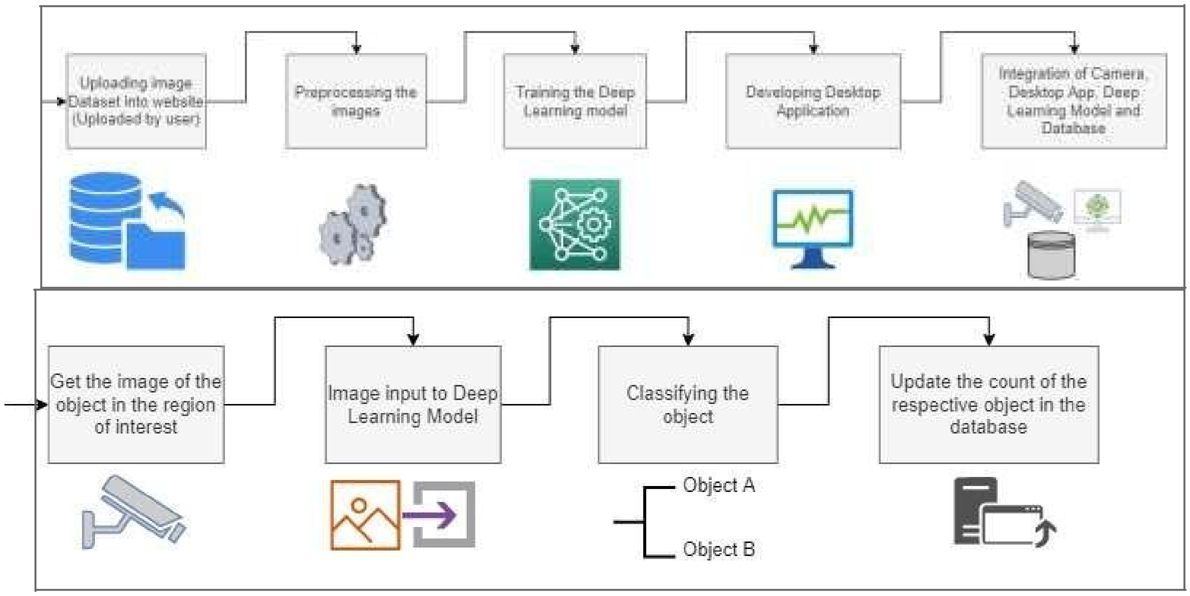

Fig.3 Real-time object counter workflow

D. Dataset

A publicly available dataset in Roboflow named Animal2–v1 comprising 9952 images belonging to classes Bear (1530 images), Deer (966 images), Elephant (1684 images), Leopard (1888 images), Monkey (1214 images), Tiger (1388 images) and Wildboar (1282 images) is used. All the images are annotated in YOLOv5 PyTorch format. The preprocessing applied for the dataset is auto-orientation of pixel data with EXIF-format stripping, and the images are resized to 416 × 416 (stretch). Here, 70% of images are used for training, 20% images for validation, and 10% images are used for testing. No image augmentation techniques are applied.

Fig. 4 Dataset Diagram

E. YOLO (You Only Look Once)

The YOLO (You Only Look Once) is a simple and extremely fast object detection algorithm that avoids a complex pipeline and considers frame detection as a regression problem (Redmon et al., 2016). YOLO processes real-time videos with a latency of less than 25 milliseconds (ms), and the mean average precision (mAP) achieved is more than twice that of other such systems. An entire image sequence is fed as input to YOLO during training and testing; thereby, the contextual information about classes and their appearance is implicitly encoded. The input image is divided into grid cells of size S × S. A grid cell is responsible for predicting B bounding boxes with five predicted values x, y, w, h, and c in each bounding box. (x, y) is the coordinate of the center point of a bounding box relative to a grid cell, w and h are the width and height of the bounding box respectively, and c is the confidence score of an object being present in a bounding box. With C class probabilities, the prediction is encoded as (S × S × (B × 5 + C)) tensor.

The final algorithm used for the model creation is YOLOv3, which is extremely fast and accurate. It is one of the popular pre-trained models which performs all the real time recognition especially with the live feeds as the input to the model.

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YOLO is widely used in many sectors. It was chosen because of its efficiency, performance, accuracy, and the recognition speed. This algorithm works by using different models for required functions like feature extraction, classification of the regions and finally by creating the bounding boxes for prediction, thus cost more utilization of CPU, time, and prediction speed. Finally, the classification of the image is also performed by dividing the images by many frames this also result in more memory utilization. But YOLO overcame these issues by dividing the total image into many frames and find the details in the image at a single process. Now the grid is considered as a unique feature and these features will give a confident score. A threshold value is set with this value; the confidence score of each grid is calculated by taking the maximum values it predicts the overall image with the given training data.

V. RESULTS AND DISCUSSION

The accuracy rates depict the reliability of identifying various wild animals. Tigers stand out with a 90% accuracy rate, snakes follow closely at 85%, while wolves and foxes exhibit an 80% accuracy rate. Lions and cheetahs maintain a 70-75% accuracy rate. With this we understand the ease of characterizing an animal due to its physical uniqueness.

Fig.5 Tiger detected on the road

Fig.6 Deer detected on the road

The practical applicability of our model in real-time situations has not been adequately assessed, particularly in the context of various atmospheric disturbances such as fog or rain, as well as during the critical low-light periods of dusk, dawn, and nighttime. Additionally, the potential ecological and ethical implications of deploying continuous monitoring systems in wildlife habitats, which may influence animal behaviour, have not been fully explored. Although the model has demonstrated effectiveness in recognizing species, its ability to interpret complex animal behaviours and interactions, which are of great ecological significance, has not been thoroughly examined. These limitations are crucial for guiding future research to enhance the model's practical utility and contribute substantially to the conservation and management of biodiversity.

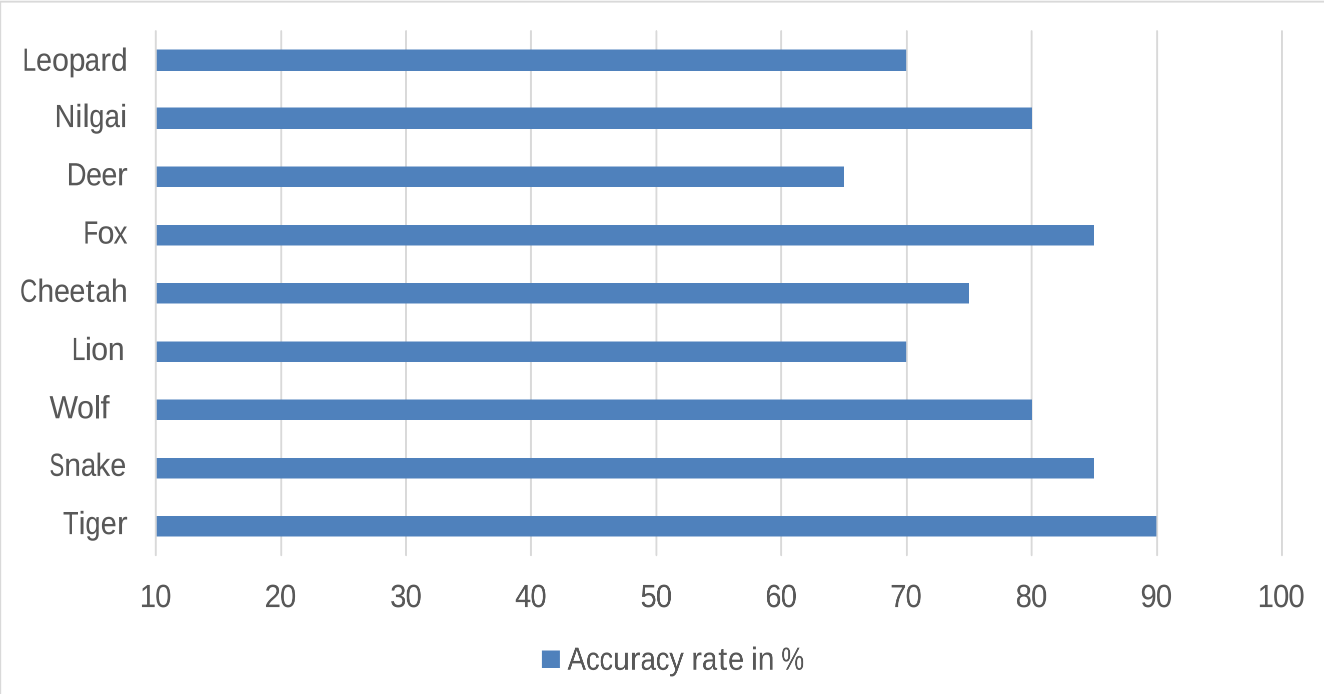

Fig 7. The accuracy of different wild animals

VI. CONCLUSION

The forest surveillance project represents a significant advancement in wildlife monitoring and conservation efforts, leveraging cutting-edge technologies to address the challenges faced by conservationists and forest officers in safeguarding natural habitats. Through the integration of deep learning, edge computing, and instant messaging platforms, the project has developed a comprehensive system capable of real-time wildlife detection, data analysis, and communication with stakeholders. By deploying surveillance cameras equipped with advanced deep learning algorithms, the project enables continuous monitoring of wildlife activity, providing conservationists with timely and accurate information about species presence, behaviors patterns, and potential threats. The integration of edge computing devices ensures efficient data processing at the source, reducing latency and enabling rapid response to detected wildlife activity.

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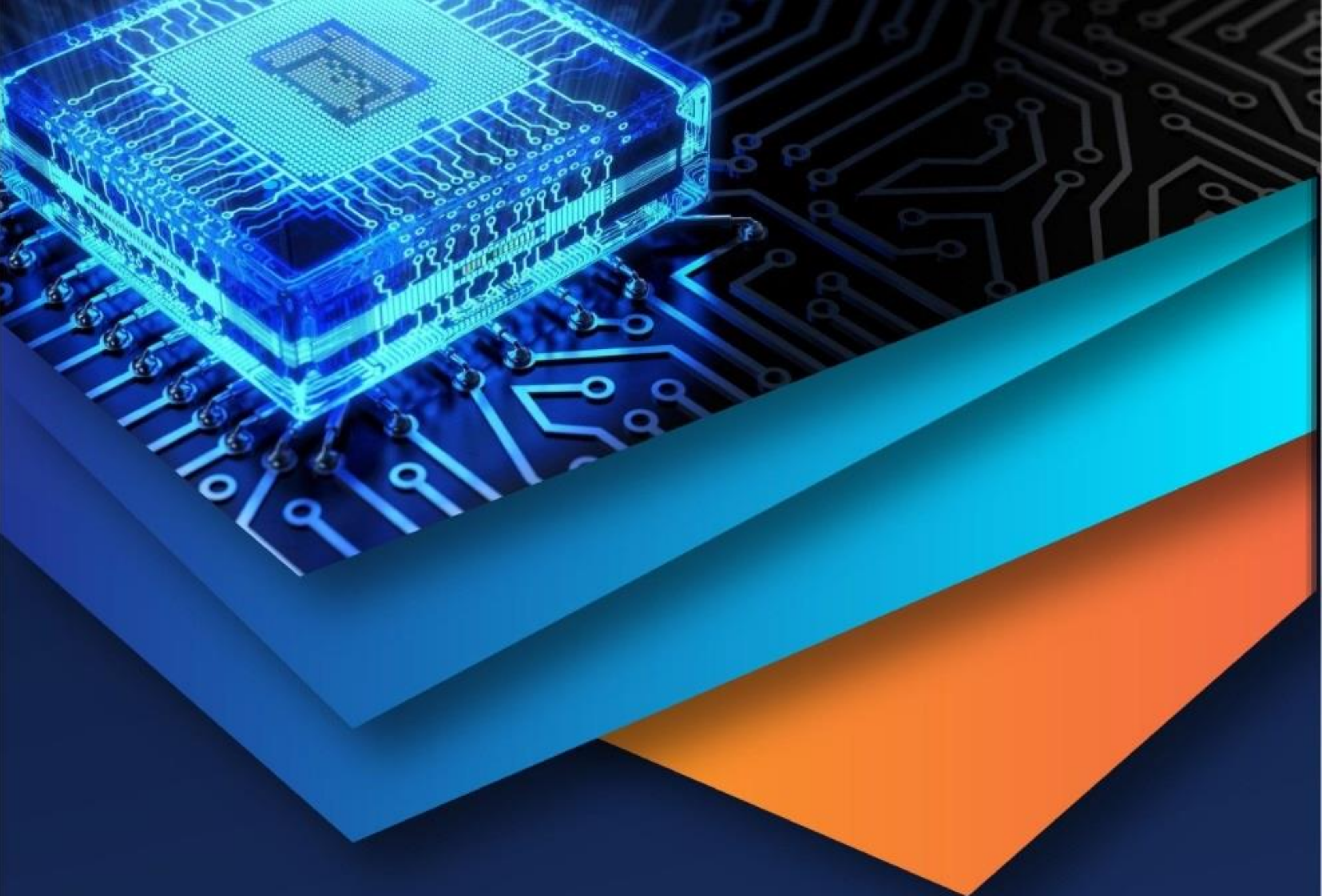

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