IOT BASED ANTI-POACHING SYSTEM WILDLIFE MONITORING SYSTEM IN REMOTE AREA

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Abstract- *Illegal poaching and deforestation cause considerable risks to biodiversity as they result in wildlife extinction and degradation of the environment. To cope with this problem, we suggest developing an IoT-Based Anti-Poaching System which will allow monitoring and detecting activities in forest regions. Our solution involves a Raspberry Pi that allows video streaming and storing videos in cloud servers in order to analyze them later. As for animal detection, a machine learning model will be used for recognition of animals and their movements. In this way, we can trace the location of animals in different territories and identify any abnormalities. Besides, we suggest using a YOLO (You Only Look Once) deep learning model which will help to detect fires as a consequence of illegal actions like poaching camps and deforestation. The live data gathered along with any suspicious activity detected including the presence of humans, sound of gun shots or fire breakouts shall automatically notify the forest department. The system also uses GPS technology to accurately locate the area where the threat is identified. With the use of IoT, deep learning and real time analysis, this smart surveillance system improves the efforts of forest conservation through automated monitoring and detection of threat. The purpose of this solution is to limit the poaching activities and secure endangered species in the ecosystem.*

Keywords- *IoT, Anti-Poaching System, Real-Time Monitoring, Raspberry Pi, Machine Learning, YOLO, Fire Detection, Wildlife Conservation, Deep Learning, Video Surveillance, Illegal Poaching, Deforestation, Smart Surveillance, Threat Detection, Automated Alerts.*

I. INTRODUCTION

The issues of poaching and deforestation have now become some of the biggest challenges in the field of wildlife conservation and ecosystem balance. Many animals may be endangered due to the uncontrolled hunting activities and destruction of their natural habitats, whereas deforestation contributes to global warming and the extinction of many other species. Manual ways of keeping track of forest zones through patrols or fixed security cameras have turned out to be ineffective because of the huge size of forest zones and insufficient financial means. Technology-based approaches involving IoT, machine learning, and deep learning have been introduced as a potential solution. The IoT based Anti-Poaching System suggested by this project uses Raspberry Pi for video streaming, machine learning for detecting animals, and YOLO (You Only Look Once) for fire detection. Raspberry Pi is an affordable and energy-efficient computing device which allows video streaming in real time and uploading of videos to cloud platform for further processing. With the use of deep learning algorithms, the system is able to differentiate between regular and abnormal behavior, thus detecting any unauthorized human activity, wildlife activity, and forest fires. The animal detection module uses machine learning models that are fed data from animal databases to detect and classify different animals within captured video frames. This functionality is important for tracking the movement of endangered animals and poaching activities. Furthermore, the fire detection module, which uses YOLO, will be able to detect fires resulting from illegal activities such as those that arise from poaching camps and deforestation. Early detection of these events will help forest officials take necessary steps to prevent extensive environmental destruction.

Once any suspicious activity is detected, the system automatically sends alerts and notifications. The alerts are sent to the authorities concerned through a mobile application or dashboard on a web portal, which also includes real-time videos, GPS coordinates, and time stamps of the event. This will allow quicker action from the authorities, and it will help them deploy patrolling teams to the area concerned very quickly. The inclusion of sound detection capability can also allow the system to recognize any sound of gunshots or any other noise to detect any illegal hunting activities.
By using the concepts of IoT, artificial intelligence, and real-time data analysis, this system offers a unique and scalable solution to wildlife protection and forest conservation. The installation of this automated system can go a long way in decreasing poaching cases, preventing deforestation, and conserving nature for our future generations. It will show the potential of combining deep learning and IoT in protecting our environment.

II. RELATED WORK

In this study, a new IoT-enabled smart wildlife monitoring system, which utilizes several types of sensors and devices to monitor environmental conditions and movement of animals in real time, is presented. The authors highlight the application of the system to monitor the changes in habitat and provide valuable data for wildlife conservation through the use of environmental sensors and GPS technologies. It is found that the use of the system considerably improves the ability to detect poaching events and, thus, helps in managing wildlife reserves effectively. [1]

The authors of the article analyze various machine learning algorithms to predict poaching incidents. They consider the efficiency of such algorithms as random forests, support vector machines, and deep learning for predicting poaching events according to past records and environmental features. It is concluded that machine learning algorithms are highly effective in predicting poaching incidents, thus helping conservationists more efficiently organize their fight against wildlife crime. [2]

This study focuses on the use of drones fitted with camera and sensor technology to conduct surveillance in wildlife reserves for any signs of poaching activities. This paper presents a methodology which incorporates the use of computer vision algorithms to detect any unusual behavior of humans in aerial images. Through case studies, this paper shows how drone surveillance can help detect any poaching activities in an efficient manner. The findings of this study indicate that the use of drones can be helpful for conservation efforts of species. [3] This research paper is about developing a mobile application for monitoring wildlife in local communities. The researchers stress that involving local communities in the conservation process becomes possible due to their capacity to report any poaching and provide evidence via the application. This research proves the positive effect of using the application for wildlife protection and raises the question of the potential of mobile technologies in this sphere. [4]

In this study, the researchers suggest an innovative approach to improving the methods of wildlife management through the use of integrated solutions which comprise Internet of Things devices and AI technologies. These include cameras and sensors, which gather information regarding the wildlife population and behavior of people. It is explained how the AI systems analyze this information in order to detect possible threats to the species like poaching and habitat degradation. This research shows that the proposed integration has the potential of greatly improving the decision-making process within wildlife management. [5]

The review research discusses the various ways of utilizing AI in animal conservation, focusing specifically on habitat assessment and poaching prevention. The researchers examine the effectiveness of using AI technologies in detecting unlawful actions and evaluating the state of ecosystems. The results show the great potential of AI technologies to increase the efficiency of animal conservation but also the necessity for further research and development in this field. [6]

The research discusses an IoT-based system that prevents poaching by tracking the conservation area and identifying any suspicious activity. There is an elaborated explanation of the system architecture involving cameras and sensors, as well as the monitoring platform. It was found that the method works to reduce the reaction time due to notification of the park ranger of the suspicious activities. [7]

The paper discusses the application of video analytics to wildlife monitoring and poacher activities detection. The authors propose a variety of approaches to analyze trail camera data in order to identify human presence and species of animals. The results obtained during the study prove the great potential of video analytics for decreasing costs and time required for monitoring of the animals. [8]

This research deals with the use of technology to increase community involvement in wildlife conservation. The authors propose case studies demonstrating the possibilities for the involvement of local communities in the process of poaching and wildlife conservation via social media and mobile apps. [9]

In the review, the authors examine the advantages and disadvantages of implementing IoT technology in the context of wildlife conservation. Some of the issues they discuss include data handling, connectivity in rural areas, and the requirement for an interdisciplinary approach. The review provides a number of successful examples of implementation of IoT technology in the process of wildlife conservation, thus suggesting some possible ways for future research in this sphere. [10]

III. PROPOSED SYSTEM

The proposed IoT-Based Anti-Poaching System will help in monitoring and protecting the wildlife and forest resources in the remote places in order to address the problems of poaching and deforestation. It involves the use of cameras and sensors placed strategically within the areas under observation. Sensors involved include acoustic sensors that detect particular sounds such as gunshots and chain saws, motion sensors that detect any kind of movement which could be against the law, and environmental sensors that detect parameters such as temperature and humidity which could indicate the presence of fires. The high resolution cameras will take clear pictures and videos in order to ensure that there is constant monitoring round the clock, and infrared cameras which detect heat sources will assist in monitoring during the night. Data gathered will then be relayed to the central server through reliable communication tools such as the ESP32 that provides reliable wireless connectivity in remote places. The central server has to analyze the collected data using machine learning algorithms.

Proposed Architecture:

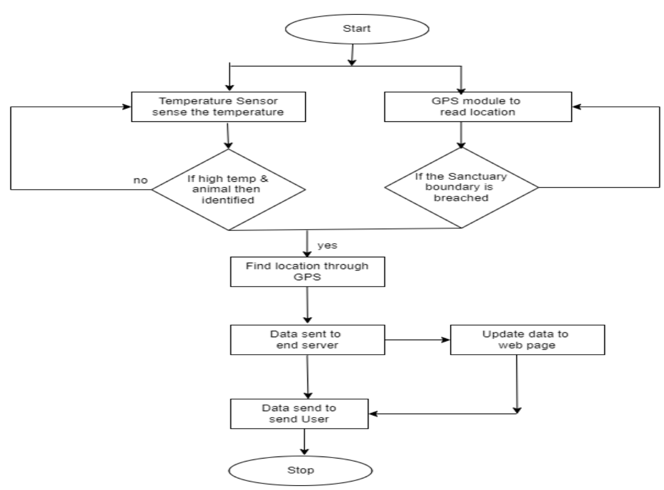


Fig.1. Proposed Architecture

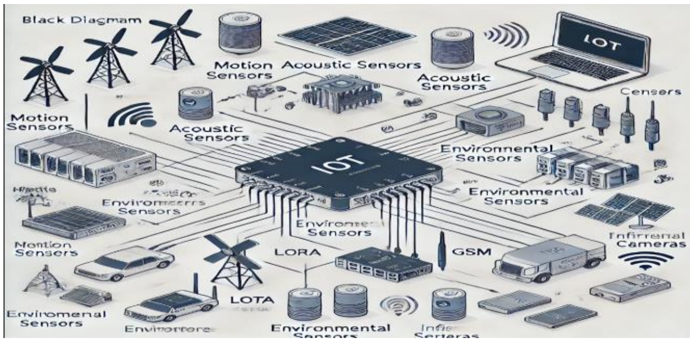


Figure2 Framework Diagram

CNN Model

A Convolutional Neural Network (CNN) is mostly used in image classification and object detection applications, hence can be used to detect animals in forests in real time. In this project, a CNN is developed which is trained to detect different species of animals in forest environments through camera videos captured using Raspberry Pi. A CNN model is comprised of several layers which include: Convolutional Layers which are used to extract spatial features of an image, Pooling layers for dimensionality reduction and fully connected layers for classification. The images undergo processes such as detecting edges and texture patterns.

The inputs of the CNN models are usually images of predetermined size such as 224×224 pixels or any other determined size. Max-pooling layers are used to down sample the feature maps for efficiency by reducing the complexity of calculations without losing any relevant information. Once the features have been extracted, they will be fed into the fully connected layers that learn the classification of various types of animals. At the output layer, a softmax activation function is used to determine the probable class of the animal. To achieve high precision, the CNN model should be trained using a huge dataset containing wildlife images. This could be publicly available data sets such as ImageNet, naturalist, or data gathered from surveillance cameras. Data augmentation methods such as flips, rotations, zooms, and changes in brightness would be employed during the training process. Also, the pixel values would be normalized between 0 and 1, and the animal classes would be labeled numerically using one-hot encoding. This network uses a categorical cross-entropy loss function for training, and optimization takes place through the Adam optimizer to ensure faster convergence and higher accuracy. After training, the CNN model can be used on Raspberry Pi for the purpose of real-time animal detection and monitoring. The Raspberry Pi captures video footage from the forest, performs processing of the images, and classifies the detected animals based on the trained model. OpenCV will be used for capturing video footage, while the model predicts the species of the animal in the footage. In case of any detection, real-time alerts and notifications could be sent to forest authorities by using a mobile application or web portal. This will help forest authorities to act accordingly to prevent poaching and other illegal activities in forests. To conclude, animal detection using CNN is essential for wildlife conservation and preventing poaching in the forests. With the use of deep learning techniques and Internet of Things, this system will provide an automated approach for wildlife monitoring in the forest environments.

YOLO Model

The You Only Look Once (YOLO) model is an object detection algorithm that performs efficiently in the detection of fire in forests. In this project, the YOLO model will be applied in the detection of fire in videos obtained from the camera mounted on the Raspberry Pi. It is important to note that the YOLO model is very fast since it can detect objects in real-time videos through its single-stage architecture. YOLO process videos by splitting them into a grid system in which different grid cells predict several bounding boxes together with confidence scores of the objects within the grid cell. To detect fires, YOLO is trained to detect flames and smoke. The algorithm is able to perform better than other approaches since it does not rely on pixel intensity changes but rather relies on feature extraction using deep learning. YOLO fire detection training dataset comprises of image samples having different kinds of fires, smokes, and non-fire scenarios in order to maintain high accuracy. These may include datasets like Flame dataset, FireNet dataset, or any other custom datasets collected from surveillance cameras for training purpose. Bounding boxes are created around fire areas in the images and training is done using loss functions to reduce localization error and false positive values. Data augmentation strategies like changing the brightness of images, introducing noises and rotations are adopted in order to improve robustness to environmental changes. After training, the YOLO model is then implemented on Raspberry Pi using OpenCV and TensorFlow or Darknet. The model continually analyzes the video frames and identifies fires instantly after their occurrence. If there is fire, then the alarm system is triggered, and alerts are issued to forest personnel or firefighters through SMS, mobile applications, or cloud monitoring systems. Also, an automatic response system can be used to initiate fire suppression systems such as sprinklers or fire retardants in areas where the risk of fire is higher.YOLO model-based fire detection offers a quick, effective, and accurate method for wildfire prevention in forest areas. This method combines deep learning technology and IoT to improve real-time monitoring and enable instant measures against fire risks. Possible improvements that can be made in the future include thermal imaging, fire surveillance drones, and artificial intelligence-based risk assessment. Raspberry Pi Zero is an affordable and efficient microcontroller which can be used in IoT-based anti-poaching and fire detection systems for the purpose of video capturing and uploading in real time. In case of integration of Raspberry Pi Zero with a Raspberry Pi Camera module, the device can capture videos and upload them on a server or cloud storage using deep learning frameworks like CNN and YOLO.

1. Hardware Setup

The setup consists of:

Raspberry Pi Zero (W/WH) – A lightweight microcontroller with Wi-Fi support.

Raspberry Pi Camera Module – A compatible camera for capturing video (e.g., Raspberry Pi Camera v2 or NoIR for night vision).

MicroSD Card – Stores the operating system and required software.

Power Supply (5V, 2A) – Provides stable power to the Raspberry Pi Zero.

Figure3 Zero Raspberry PI

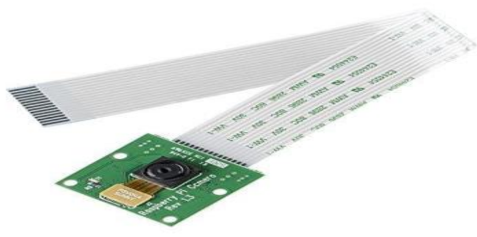


Figure 4 Raspberry PI Camera Module

The Raspberry Pi Camera Module is a compact, high-resolution camera designed for capturing images and videos in Raspberry Pi-based projects. It connects to the Raspberry Pi's CSI (Camera Serial Interface) port, enabling high-speed data transfer. In IoT-based anti-poaching and fire detection systems, this module plays a crucial role in video surveillance, real-time monitoring, and AI-based detection of animals and fire.

1.Result and discussion

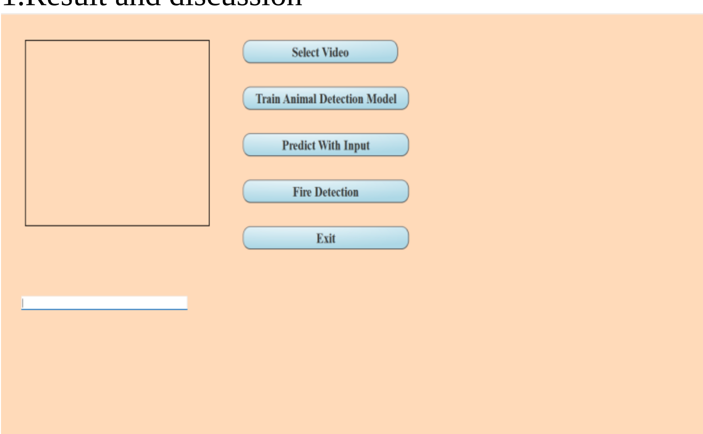


Figure 5 Main UI Part

The figure 5 shows the main UI part where user can select the video, train the model and predict animal and fire.

2. CNN Model Accuracy Training and validation

Figure 6 Training VS Validation Accuracy

The figure 6 consists of two plots: **Training vs. Validation Accuracy** (left) and **Training vs. Validation Loss** (right). These plots represent the performance of a machine learning model, likely a CNN, during training over 10 epochs. In the **Training vs. Validation Accuracy** plot, the training accuracy (blue line) rapidly increases, reaching nearly 100% by epoch 5, while the validation accuracy (red line) improves more gradually, peaking around 80% at epoch 10. This suggests that the model is learning well on the training data but may be experiencing some overfitting, as the validation accuracy does not reach the same level as training accuracy. In the **Training vs. Validation Loss** plot, both the training loss (blue line) and validation loss (red line) decrease over epochs, indicating that the model is learning effectively. However, the gap between them suggests potential overfitting, as the validation loss remains consistently higher than the training loss. Overall, while the model shows strong learning performance, the difference in training and validation accuracy and loss suggests that improvements such as **regularization, dropout, or more data augmentation** may help generalize better to unseen data.

3. Confusion Matrix

The classification results of the CNN model describe its performance metrics. The proposed CNN model achieves an accuracy of 90%, which is calculated by comparing the actual values with the predicted values. Accuracy is determined using the formula:

$$\text{Accuracy} \;= TP + TN/TP + TN + FP + FN$$

Precision: It can be described by the range of accurate results the model produced or by the proportion of all positive categories that the model accurately predicted were really true. The precision in the aforementioned figure is 70%. It can be computed using the formula below.

$$\text{Precision} \;= TP/(TP + FP)$$

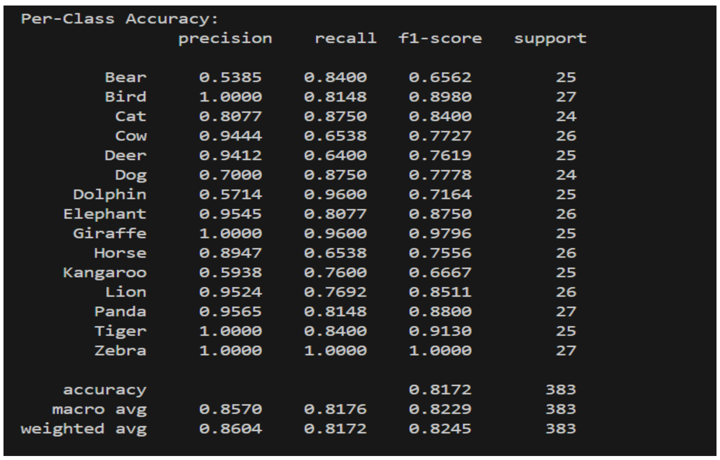
Recall: It's outlined because the out of total positive categories, however model expected properly. The recall should be as high as doable. Our suggested system has a recall of $0.67.\%$

$$\text{Recall} = TP/(TP+FN)$$

F1-Score: The F1-score is a harmonic mean of precision and recall, providing a balance between the two metrics. It is useful when dealing with imbalanced datasets. The F1-score for this model is 0.72, computed as:

$$F1S\text{ core } = 2\times\left(\frac{\text{Precision } \times \text{ Recall}}{\text{Precision } + \text{ Recall}}\right)$$

These evaluation metrics help in understanding the effectiveness of the CNN model in classification tasks. While the model has a good precision, its recall suggests that further improvements can be made to enhance its ability to correctly detect positive instances.



Per-Class Accuracy:

	precision	recall	f1-score	support
Bear	0.5385	0.8400	0.6562	25
Bird	1.0000	0.8148	0.8980	27
Cat	0.8077	0.8750	0.8400	24
Cow	0.9444	0.6538	0.7727	26
Deer	0.9412	0.6400	0.7619	25
Dog	0.7000	0.8750	0.7778	24
Dolphin	0.5714	0.9600	0.7164	25
Elephant	0.9545	0.8077	0.8750	26
Giraffe	1.0000	0.9600	0.9796	25
Horse	0.8947	0.6538	0.7556	26
Kangaroo	0.5938	0.7600	0.6667	25
Lion	0.9524	0.7692	0.8511	26
Panda	0.9565	0.8148	0.8800	27
Tiger	1.0000	0.8400	0.9130	25
Zebra	1.0000	1.0000	1.0000	27
accuracy			0.8172	383
macro avg	0.8570	0.8176	0.8229	383
weighted avg	0.8604	0.8172	0.8245	383

Figure 7 Confusion matrix

The figure 7 shows a classification report, showcasing the precision, recall, F1-score, and support for different animal classes in a machine learning model's performance. Each row represents a distinct class, detailing how well the model performs in identifying that specific class. Precision measures the proportion of correct predictions among all predicted instances of a class, while recall assesses how well the model captures all actual instances of that class. The F1-score is the harmonic mean of precision and recall, providing a balanced performance metric. The model performs exceptionally well for certain classes such as "Bird," "Giraffe," "Tiger," and "Zebra," achieving perfect precision and recall, whereas classes like "Bear" and "Kangaroo" exhibit relatively lower scores, indicating challenges in classification. The overall accuracy of the model is 81.72%, with macro and weighted averages also reflecting strong performance. The weighted average considers class imbalances, making it a more reliable indicator of the model's effectiveness across different classes.

Figure 8 Animal Detection

The figure 8 shows the animal detection. When the animal is detected the system buzzer is on.

4. Fire Detection

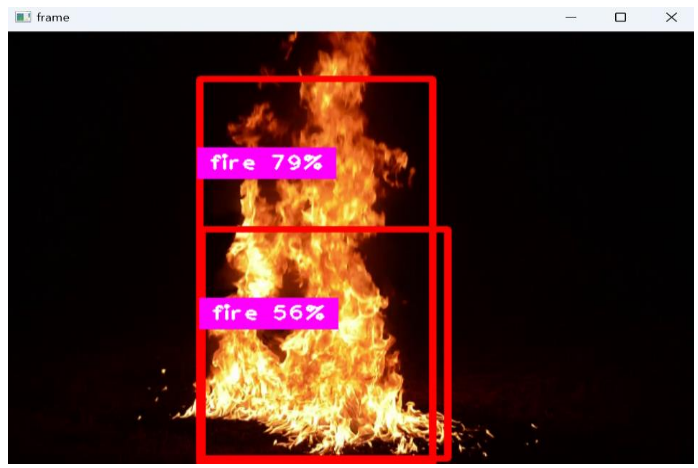


Figure 9 Fire Detection

The figure9 shows the fire detection from inputted video. When the fire is detected the system buzzer is on.

5. Accuracy Over Epoch

Table 1 Accuracy over epoch

Epoch	Accuracy
10	82.77 %
30	90.20 %
50	93.56 %

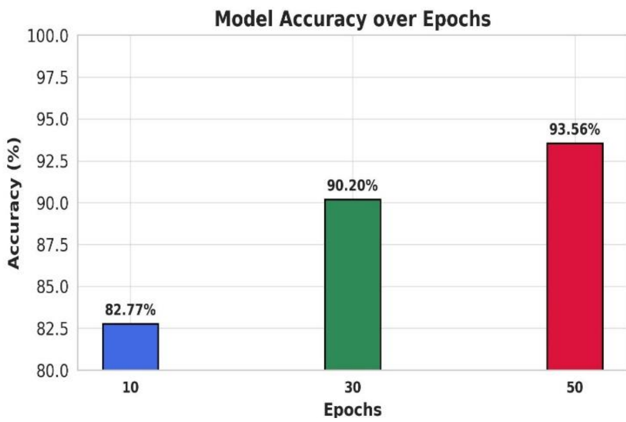


Figure10 Model Accuracy over epoch

The bar graph in Figure 10 shows the development of accuracy for the machine learning algorithm for various epochs such as 10, 30, and 50. Here, the number of epochs is plotted on the X-axis, while accuracy percentage is plotted on the Y-axis. As depicted in the graph, the accuracy increases gradually from 82.77% for 10 epochs to 90.20% for 30 epochs, and finally up to 93.56% for 50 epochs. All the bars in the graph are represented with colors, and numerical values are provided above each bar.

Conclusion

The implementation of an IoT-based Anti-Poaching Activity Detection System provides a real-time and intelligent approach to wildlife protection. By leveraging Raspberry Pi with a camera module for video streaming, CNN-based machine learning models for animal detection, and YOLO for fire detection, the system ensures continuous monitoring of protected areas. The integration of cloud storage, real-time alerts, and AI-based analysis enhances the system's ability to detect and respond to potential threats effectively. Implementation of IoT based Anti-Poaching Activity Detection System is an intelligent solution to ensure real-time wildlife safety. Using Raspberry Pi with a camera module to stream videos, CNN-based machine learning models to detect animals, and YOLO to detect fires will ensure constant monitoring of the wildlife conservation area. Cloud storage, real-time alerts, and AI-based analytics improve the effectiveness of the system.

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