Animal Enchroachment Detection in Croplands using Machine Learning Approaches

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ABSTRACT

Animal Enchroachment is a major threat to the productivity of the crops, which affects food security and reduces the farmer's profit. Machine learning-based solutions are used to overcome this problem. Convolu- tional Neural Network (CNN), ResNet-50, and Inception v3 are the three methods used to identify the animals. The proposed model classifies the detected animals and alerts humans through a message to avoid animal intru- sions into properties. Hence, minimising the dangerous consequences caused by the intrusion. The Inception v3 model provides more accurate results compared to the other two models, and it is considered the main method for the proposed model.

Keywords: Convolutional Neural Network, ResNet-50, Inception V3, Machine learning.

INTRODUCTION

Agriculture is the most important sector in India. Day by day, the production of crops is decreasing due to a lack of interest in farming. The major problem faced in farming is animal intrusion. The animals cause damage to the crop and also reduce the productivity of farmers. In this situation, we need a proper detection system to detect the pres- ence of animals. By knowing which animal is most likely to come into cropland, farmers can use good prevention methods to keep the animals away from croplands. Traditional methods are harmful to ani- mals and humans, time-consuming, and lead to the need for more elaborate solutions. Machine learn- ing with convolutional neural networks, ResNet 50, and Inception v3 models offers a promising approach to this problem. Animal infestations are always a problem for farmers. Sheep, cows, ele- phants, monkeys, etc. roam the fields without the consent of the farmer and destroy and eat the crops. By doing so, the yield could consequently expe- rience a substantial loss, prompting the purchase of further financial insurance to pay for the harm. Every farmer should be aware of the animals in the area who need to be protected from suffering while using their land to grow food. Right away, this issue needs to be addressed, and a workable solution needs to be developed and implemented.

RELATED WORKS

Mowen Xue et al.[1] Developed a technique for aerial animal surveillance. Mainly focuses on the difficulties of identifying small animals from aerial images, where creatures may seem like small and far-off objects due to the altitude of the aerial platform. This approach integrates super-resolution and altitude data exploitation directly into deep animal detection pipelines for aerial survey appli- cations.

T. Sandeep et al.[2] They proposed a prototype that can be used as software that recognises ani- mals and classifies them accordingly. The software required can be developed using openCV and deep learning algorithms. This can be embedded with an ultrasonic repellent hardware system that drives the animal away from the farm and also informs the farmer about this. This is a low-cost project that aims to drive the animals away without causing any lethal harm.

Davide Adami et al.[3] The proposed system is based on IoT platforms that provide a sat- isfactory

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compromise between performance, cost and energy consumption. More specifically, in this work, we deployed and evaluated various edge computing devices running real-time object detector (YOLO and Tiny-YOLO) with custom- trained models to identify the most suitable animal recognition Hardware or Software platform to be integrated with the ultrasound generator.

K Balakrishna et al.[4] The authors propose an integrated system that combines IoT and machine learning for crop protection against animal intru-sion. The system consists of sensor nodes that are deployed in the field to collect data on environ- mental parameters such as temperature, humidity, soil moisture, and animal presence. These sensor nodes are connected to a central hub or gateway through wireless communication, forming an IoT network.

Devsmit Ranparia et al.[5] Developed a system that uses audio data to detect the presence of wild animals and trigger repelling actions. The system consists of microphones that capture audio data from the field, which is then processed using machine learning algorithms to identify animal vocalisations or sounds associated with animal presence.

Kuei Chung Chang et al.[6] The authors propose an IoT-based system that utilises object detection and tracking techniques to monitor and detect the presence of monkeys in agricultural fields. The proposed system consists of IoT devices, such as cameras or sensors, that are deployed in the field to capture images or data related to the presence of monkeys. These devices are connected to a central hub or gateway through wireless communication, forming an IoT network.

METHODOLOGIES

Convolutional Neural Nework(CNN)

CNN models can be used for animal intrusion detection in cropland by training the model to recognise images or video footage captured by cameras installed in the cropland. The CNN model can learn to differentiate between different types of animals and identify their locations within the cropland. To develop an effective animal intrusion detection system using CNN, a large dataset of labelled images or videos of animals in cropland would need to be collected. The dataset can be used to train the CNN model, which can learn to recognise the features of different animals and their behaviours. Once the CNN model is trained, it can be used for real-time animal intrusion detection by analysing the video feed from the cameras installed in the cropland. The model can detect when an animal enters the cropland and identify the type of animal and its location. This information can be used to trigger an alarm or send alerts to farmers or farm managers, allowing them to take immediate action to prevent crop damage.

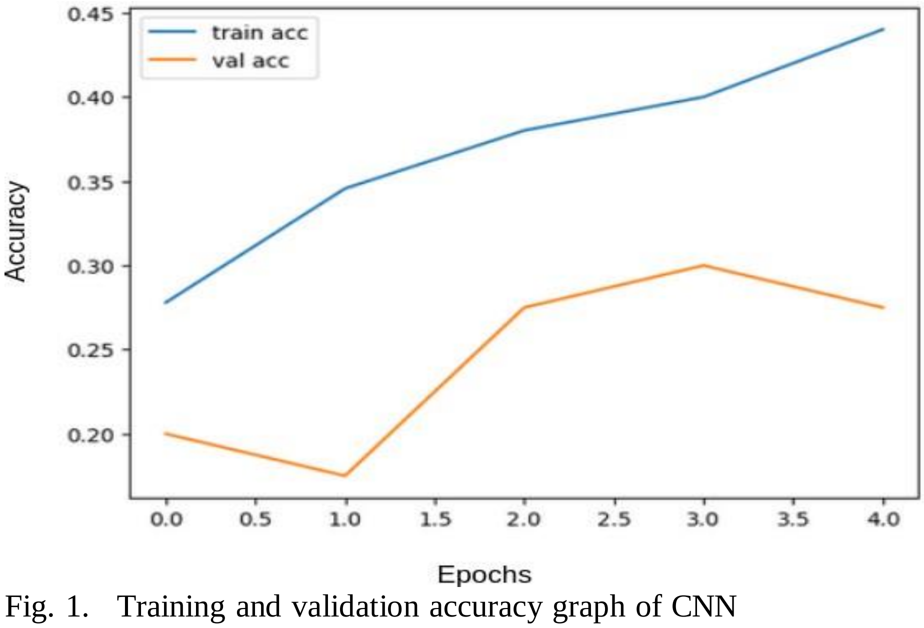

Fig. 1. Training and validation accuracy graph of CNN

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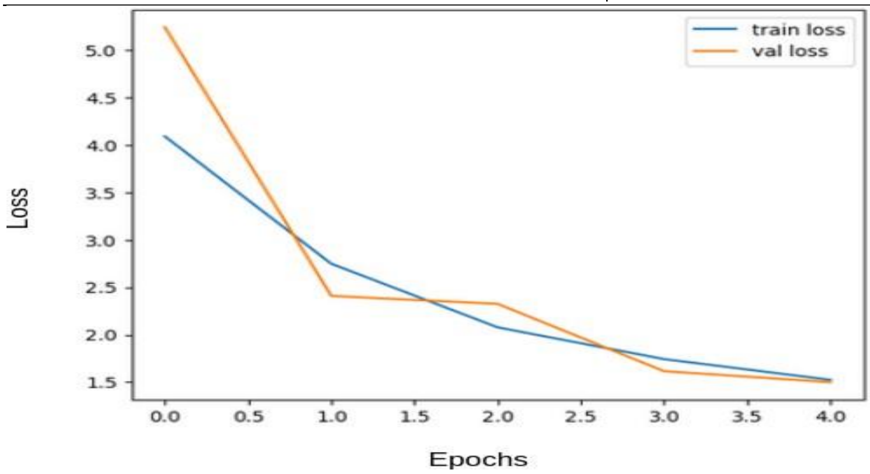

Fig. 2. Training and validation loss graph of CNN

ResNet 50

ResNet-50, a well-known deep neural network design, can be used as a machine learning method to identify animal encroachment on agricultural lands. It has been shown that the deep convo- lutional neural network ResNet-50 excels in a wide range of picture categorization tasks. It is a popular choice for many computer vision applica- tions, including the detection of animal trespass in agriculture. A dataset of photos taken by cameras installed in crops for the purpose of detecting animal intrusions can be used to train ResNet-50. The network may be taught to classify photos as either including animals or not based on the visual traits of the animals in the image.

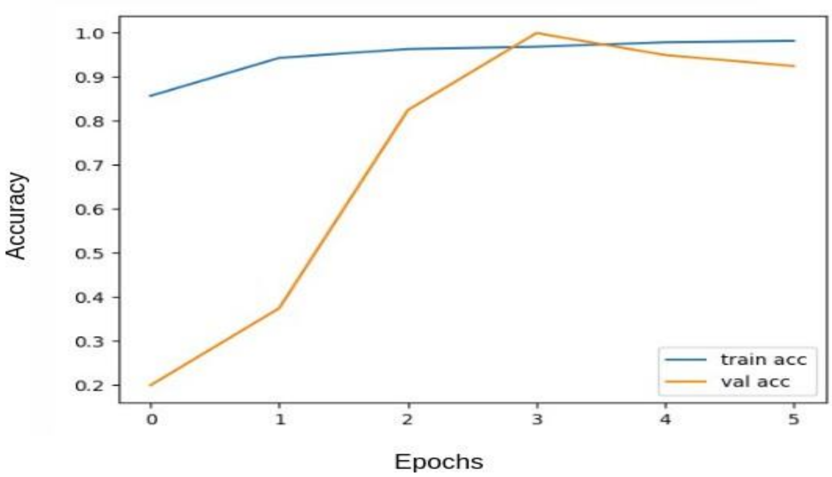

Fig. 3. Training and validation accuracy graph of ResNet 50

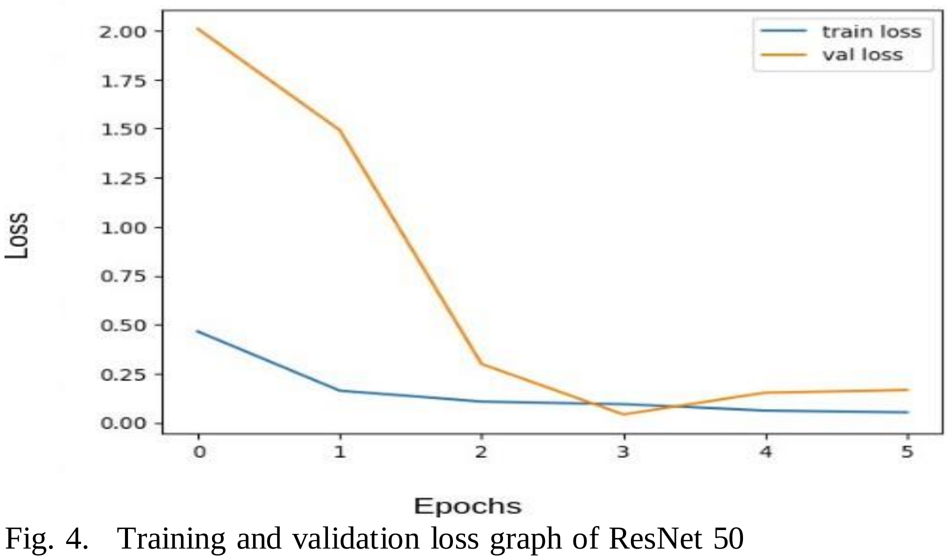

Fig. 4. Training and validation loss graph of ResNet 50

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Inception v3

Inception v3, which is a popular deep neural network architecture, can also be used for animal intrusion detection in croplands using a machine learning approach. The Inception v3 model works by using multiple convolutional layers with dif- ferent kernel sizes to extract features from in- put images. These features are then concatenated and fed through additional convolutional and fully connected layers to make the final classification decision. To use Inception v3 for animal intru- sion detection in cropland, the model is typically first trained on a large dataset of images that includes animals. During training, the model learns to recognise the visual features of animals and distinguish them from other objects. Once the Inception v3 model is trained, it can be used to classify new images captured by cameras in the cropland. The input image is fed into the model, and the model outputs a probability distribution over different classes, indicating the likelihood that the image contains animals. The Inception v3 model can be fine-tuned on a smaller dataset of images specifically related to animal intrusion detection in cropland, which can help improve the accuracy of the system. Additionally, transfer learning techniques can be used to further improve the performance of the model by adapting it to the specific characteristics of the cropland envi- ronment.

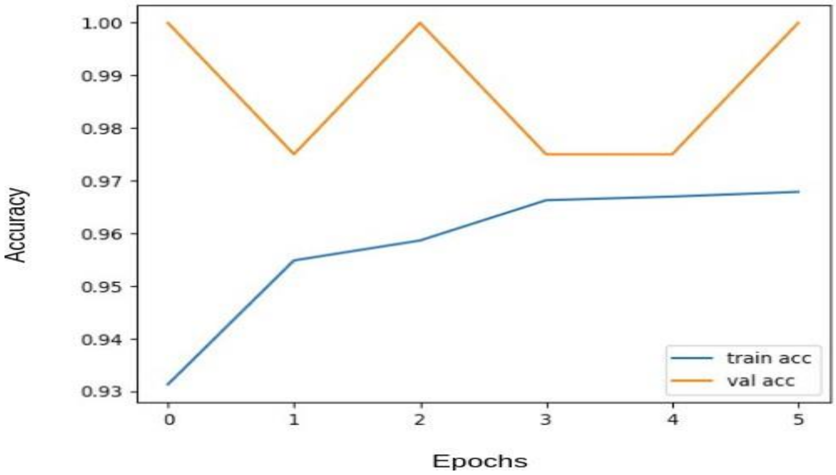

Fig. 5. Training and validation accuracy graph of Inception v3

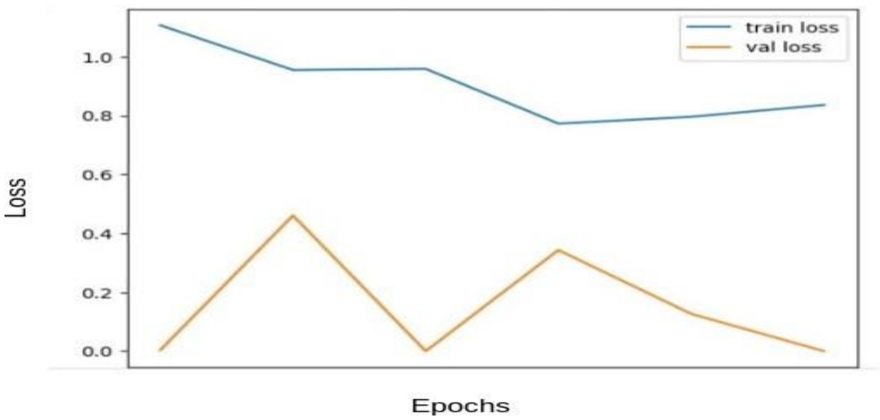

Fig. 6. Training and validation loss graph of Inception v3

PROPOSED METHOD

To address the problem of animal intrusion in cropland, propose a method that utilises CNN (convolutional neural networks), ResNet 50, and Inception v3 models. This approach involves train- ing these models on a large dataset of images con- taining various animals that are commonly found in crop fields. By fine-tuning the pre-trained mod- els, they achieve high accuracy in detecting animal intrusion in real time. Once the model is trained, it can be used to detect animals in real-time by processing images captured by cameras placed in the cropland. When an animal is detected, an alert can be sent to the farmer or a control system, triggering appropriate actions to deter the animal and prevent crop damage. Compared to traditional methods like fence-based systems, machine learn- ing approaches using CNN can be less expensive and more flexible, as they do not require

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physical barriers to be installed. They can also provide more accurate and reliable detection by analysing multiple factors, such as animal size, shape, and movement patterns.

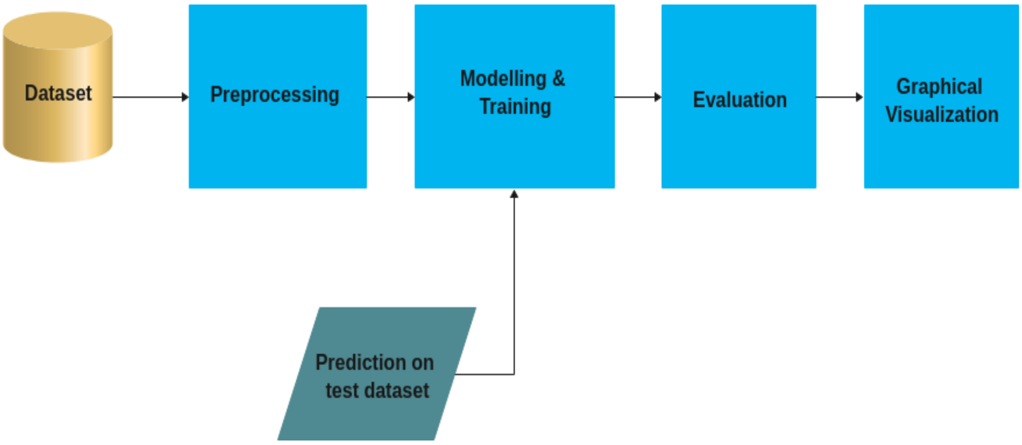

Fig. 7. Architecture of Proposed Method

Dataset

The data used in this work was an animal's image. Here, use six classes of animal images: chicken, cow, elephant, monkey, scoiattolo (squir- rel), and sheep. After collecting the images of these six classes, divide the data into training and testing data sets. Initially, five classes were used for modelling (chicken, cow, elephant, scoiattolo (squirrel), and sheep). After selecting the final model, use the six classes of dataset. The collected images of the above classes were used as a dataset for data training and testing.

Fig. 8. Dataset

Data preprocessing

The collected images need to be preprocessed to ensure that they are all of the same size and format. This can involve resizing the images, converting them to grayscale or RGB, and normalising the pixel values. Splitting the data into training, valida- tion, and test sets. Data augmentation techniques, such as rotation, flipping, and zooming, can also be applied to increase the diversity of the data and improve the model's generalization ability.

Modelling and Training

Convolutional Neural Network (CNN), ResNet 50, and Inception V3 are the models used for training the data (preprocessed data). The model that provides the highest accuracy in testing is considered the final model for animal intrusion detection in cropland. During training, the model learns to recognise features that distinguish an- imals and also to distinguish between different types of animals.

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Testing the model

Once the model is trained, it needs to be tested on a separate set of images that were not used during training. This helps to ensure that the model can generalize to new images.

Evaluation

Here, consider the F1 score, test accuracy, val- idation, and train accuracy, validation, and train loss. The Inception v3 model provides good accu- racy and less validation and train loss.

Graphical Visualization

Once the model is tested and validated, it can be saved. In this step, show the confusion matrix, ROC curve of used models, validation accuracy, validation loss, training accuracy, and loss graphs. The model was uploaded to Visual Studio Code to create the front end.

Requirements are

IMPLEMENTATION

Animal Intrusion Detection in cropland using Machine Learning approach used Inception v3 as a model because Inception v3 provides higher accuracy compared with CNN, ResNet-50 models. First, collect a dataset of animals that damage the croplands. After the data collection, import the libraries required for animal intrusion detection. Inception v3 is used as a model to create a data generator. The training and testing datasets are added to this data generator. Data generators are commonly used in animal intrusion detection sys- tems to generate labelled training data for machine learning algorithms. These algorithms are trained to distinguish between normal animal behaviour and anomalous behaviour that may indicate intru- sion or potential threats. Next, train the model (Inception v3) and save the trained model, then do the graphical visualisation, which includes valida- tion and train loss graphs and validation and train accuracy plotting. Create the classification report and predict the images from the test data. Then check the confusion matrix, plot the ROC curve, accuracy, and f1-score, and test the accuracy of the model. These are the evaluation procedures for animal intrusion detection in cropland. After the evaluation process, use the Visual Studio code. The saved model is uploaded to the Visual Studio code to create the front end. HTML (HyperText Markup Language), CSS (Cascading Style Sheets), and JavaScript are the programming languages used to create the front end and run the programme on the local host and get the outputs. To receive alerts when an animal is located, connect a mo- bile device. This makes use of both the Firebase cloud service provider and the WhatsApp API. Firebase Cloud Messaging (FCM) enables a secure and power-efficient connection between the server and devices for the free delivery and receiving of messages and notifications on iOS, Android, and the web. The Pyrebase library, which may use a configuration dictionary to interact with the Firebase platform, is used to initialise a Firebase app, which is afterwards used to authenticate a user by logging in with an email and password. After a successful sign-in, it receives the account information for the authenticated user.

RESULTS

The saved model is uploaded to Visual Studio Code to create the front end. The Inception v3 model was selected as the final model because it provides better accuracy compared to the other two models used here. HTML (HyperText Markup Language), CSS (Cascading Style Sheets), and JavaScript are the programming languages used to create the front end, run the programme on the local host, and get the outputs. The output is given below. After the prediction, the system provides an alert to the user via mobile phone.

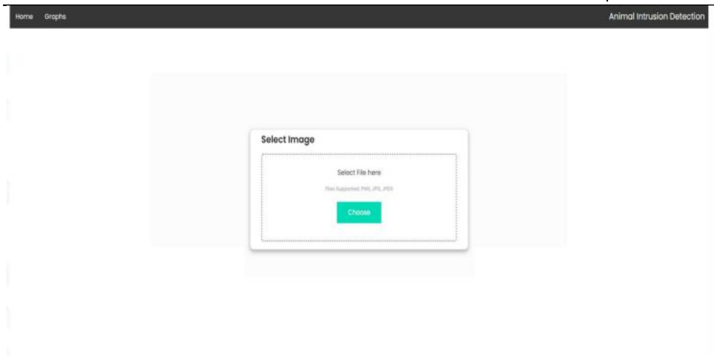

Fig. 9. Select an image

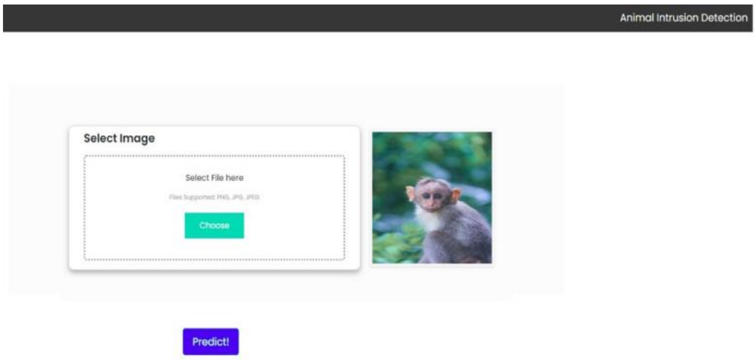

Fig. 10. Upload an image

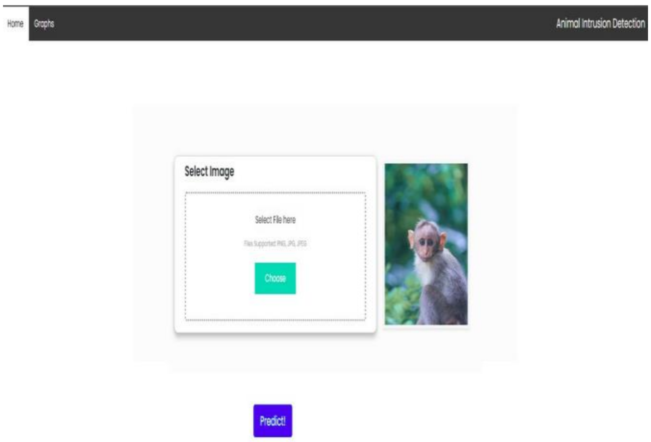

Fig. 11. Predict the image

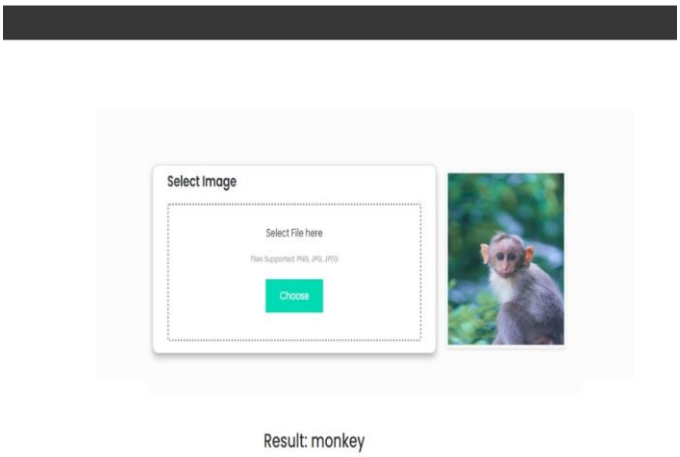

Fig. 12. Prediction result

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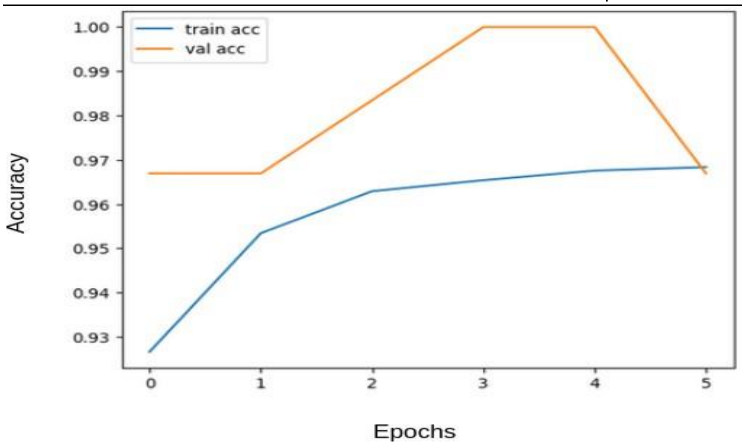

Fig. 13. Training and validation accuracy graph of final model

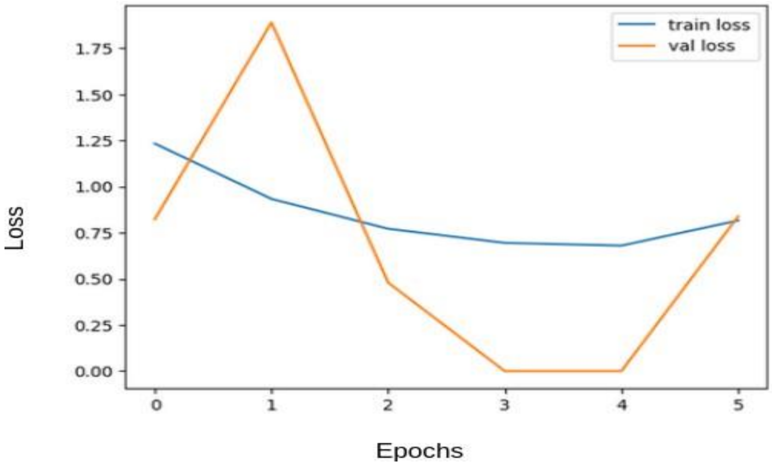

Fig. 14. Training and validation loss graph of final model

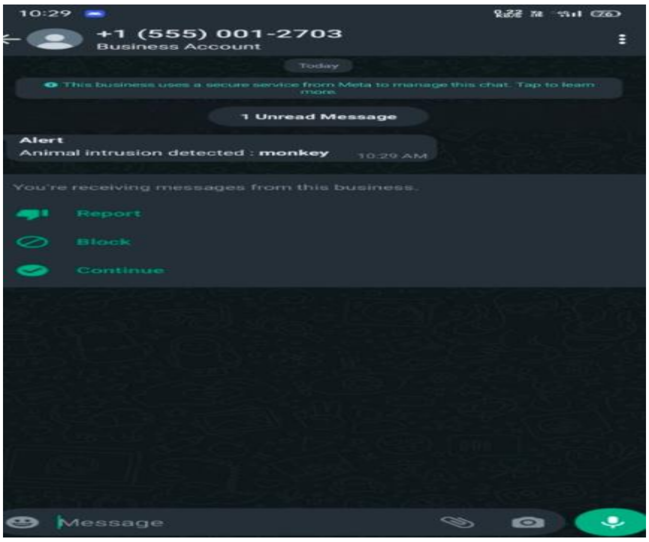

Fig. 15. Alert

CONCLUSION

The proposed system can help farmers monitor their fields and protect their crops from damage caused by animals such as chickens, cows, sheeps, elephants, and monkeys and squirrels. By using machine learning algorithms to analyse images captured by cameras installed in the cropland, the system can learn to recognise the features of animals and distinguish them from other objects in the images. This approach can improve the accu- racy and efficiency of animal detection, reduce the need for manual monitoring, and enable farmers to respond quickly to potential threats to their crops. Ultimately, the goal is to help farmers reduce crop losses and increase yields, leading to improved food security and economic benefits.

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