IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
Impact Factor: 7.67
Volume 5, Issue 7, March 2025

Wild Animal Deterrent System for Crop Protection: Leveraging TensorFlow IoT-based Acoustic Classification System

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Abstract: *The protection of crops from damage by wild animals poses a significant challenge for farmers worldwide. To address this issue while promoting non-violent coexistence with wildlife, this project focuses on the development and implementation of an intelligent wild animals' deterrent system. We employed various deep learning techniques, training several convolutional neural network models, including VGG16, ResNet50, DenseNet121, EfficientNetB0, EfficientNetB1, EfficientNetB2, Xception, InceptionV3, MobileNetV2, NASNetMobile, and NASNetLarge, using transfer learning, fine-tuning and by integrating night vision images into the dataset comprising 13 common wild animal classes known for farmland intrusion. Upon detection of an animal, the system triggers an ultrasonic alarm to repel the specific animal without causing harm. Furthermore, real-time notifications containing images of the detected animal, its type, and timestamp are sent to the farmer's mobile device, enabling prompt action to protect crops.In the pursuit of effective crop protection, this project emphasizes both accuracy and humane deterrence. The utilization of deep learning, specifically NASNetLarge model, ensures robust animal detection capabilities, even in challenging lighting conditions commonly encountered in agricultural environments. The inclusion of night vision images enriches the dataset, enhancing the model's ability to discern animals accurately. The integration of an ultrasonic alarm system offers a non-invasive method of repelling animals, minimizing crop damage without resorting to physical harm. Moreover, the real-time notifications empower farmers with timely information, enabling swift responses to potential threats. Overall, this project represents a comprehensive solution for mitigating crop damage by wild animals while fostering sustainable coexistence between agriculture and wildlife.*

Keywords: component, formatting, style, styling, insert (key words)

I. INTRODUCTION

Wildlife interference in agriculture results in substantial economic losses, prompting the need for effective deterrent systems. Traditional methods such as fencing and chemical repellents are often ineffective and can disrupt local ecosystems. Recent advancements in machine learning and IoT technologies present new opportunities for developing intelligent deterrent systems. This study explores the design and implementation of an IoT-based acoustic classification system using TensorFlow, aimed at protecting crops from wildlife.

The "Wild Animals Deterrent System for Crop Protection" project represents a pioneering endeavour in the realm of agricultural technology, harnessing the power of deep convolutional neural networks (DCNN) to address the longstanding issue of wildlife intrusion in farm environments. By employing a sophisticated classification algorithm, this system endeavours to accurately detect a diverse range of animal species depicted in images captured within agricultural landscapes. Leveraging advanced techniques such as transfer learning, fine tuning and night vision simulation, the system enhances its detection capabilities, ensuring robust performance across varying lighting conditions and environmental contexts. Upon identifying an intruding animal, the system deploys specific sound signals tailored to each species, effectively repelling them from the crops while prioritizing non-invasive and humane methods of wildlife management. Additionally, real-time notifications containing images of the detected animal, along with its

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type and timestamp, are sent to the farmer's mobile device, enabling prompt action and informed decision-making. This innovative approach not only mitigates crop damage but also fosters harmonious coexistence between agriculture and wildlife, aligning with the principles of sustainable farming practices. Through its integration of deep learning technology, intelligent sound emission, and real-time communication with farmers, the Wild Animals Deterrent System emerges as a vital tool in enhancing agricultural productivity, resilience, and environmental stewardship in the face of wildlife-related challenges.

II. TRADITIONAL DETERRENTS AND LIMITATIONS

Traditional methods for deterring wildlife from agricultural areas have been in use for many years, with a variety of techniques employed to keep animals away from crops. These methods generally include physical barriers, visual deterrents, and chemical repellents. While each of these techniques has been used with varying degrees of success, they often fall short in effectively managing wildlife intrusion due to the intelligence and adaptability of many animal species. Understanding the types of traditional deterrents and their limitations is crucial for evaluating their effectiveness and for identifying areas where modern technologies could offer improvements.

A. Fencing

Fencing is one of the most commonly used traditional methods for protecting crops from wildlife. It functions as a physical barrier designed to prevent animals from accessing agricultural fields. Different types of fencing have been developed to address various challenges, and their effectiveness can vary based on the type used, the species targeted, and the specific environmental conditions.

Electric Fences: These fences use an electric current to deter animals by delivering a mild shock upon contact. They are designed to make the animals associate the fence with discomfort, thus discouraging them from crossing it. Electric fences are often used to manage species such as deer and wild boars

Figure 1: Electric fence

Barbed Wire Fences: Barbed wire fences are constructed with sharp wire strands intended to cause discomfort or injury if animals attempt to breach the barrier. They are generally used for larger animals like cattle and deer, and are noted for their ability to withstand physical pressure.

Figure 2: Barbed wire fence

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Mesh Fences: Made from various mesh sizes, these fences aim to prevent animals from passing through by creating a physical obstruction. Mesh fences can be tailored in height and mesh size to accommodate different types of animals, including smaller species.

Figure 3: Mesh fence

Despite their widespread use, traditional fencing methods have several limitations. Electric fences require regular maintenance to ensure that the electric current remains effective, as animals can sometimes break through or bypass the fence if it is not properly maintained. Barbed wire fences, while durable, may still be breached by particularly strong or persistent animals, and can also pose risks of injury to both animals and humans. Mesh fences, though effective against smaller animals, often require additional reinforcement to be effective against larger species and may suffer from wear and tear over time.

B. Limitations of existing system

- **Lack of Real-Time Detection:** Both traditional methods and emerging technologies may suffer from a lack of real-time detection capabilities, leading to delayed responses and increased crop damage.
- **Harmful to Wildlife:** Certain traditional methods and emerging technologies may pose risks to wildlife by causing harm or injury, contradicting principles of ethical wildlife management.
- **High Maintenance Requirements:** Traditional methods often require frequent maintenance, increasing operational costs and labor requirements for farmers. Emerging technologies may also require specialized expertise and ongoing maintenance.
- **Scalability and Cost:** Both traditional and emerging technologies may face challenges in scalability and cost-effectiveness, particularly for small-scale farmers with limited resources, hindering widespread adoption and effectiveness.

C. The Impact of Wildlife on Agriculture

Wildlife can devastate crops, leading to:

- **Economic Losses:** Farmers may lose a significant portion of their yield, affecting their income and livelihood.
- **Increased Labor Costs:** Farmers often spend additional time and resources trying to mitigate wildlife damage.
- **Environmental Concerns:** Traditional deterrents can harm non-target species and disrupt local ecosystems.

III. METHODOLOGY

The "Wild Animals Deterrent System for Crop Protection" project introduces an innovative approach to mitigate crop damage caused by wildlife intrusion in agricultural settings. Leveraging advanced technologies such as deep learning and intelligent sound emission, our system offers real-time detection and humane deterrence of wild animals, ensuring the safety and integrity of crops without causing harm to wildlife. The system utilizes a deep convolutional neural network (DCNN) classification algorithm, specifically a NASNetLarge model, for accurate detection and recognition of various animal species from images captured by cameras installed in farm landscapes. Additionally, an ultrasonic alarm sound is emitted to repel detected animals without causing physical harm. Real-time notifications, including images of

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the detected animal, its species, and timestamp, are sent to the farmer's mobile device for prompt action. Night vision simulation is incorporated to enhance accuracy, enabling effective detection even in low-light conditions.

A. System Architecture

An architectural diagram is a diagram of a system that is used to abstract the overall outline of the software system and the relationships, constraints, and boundaries between components. It is an important tool as it provides an overall view of the physical deployment of the software system and its evolution roadmap. The system architecture of the proposed system is given in the figure 4 given below.

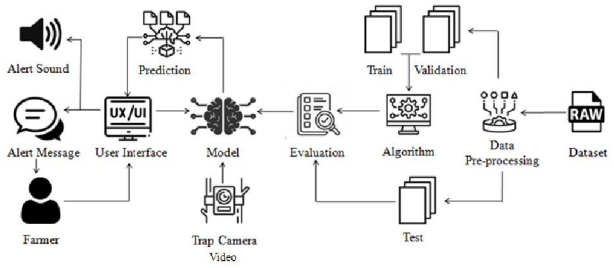

Figure 4: System Architecture

A use case diagram at its simplest is a representation of a user's interaction with the system that shows the relationship between the user and the different use cases in which the user is involved. A use case diagram can identify the different types of users of a system and the different use case will often be accompanied by other types of diagrams as well.

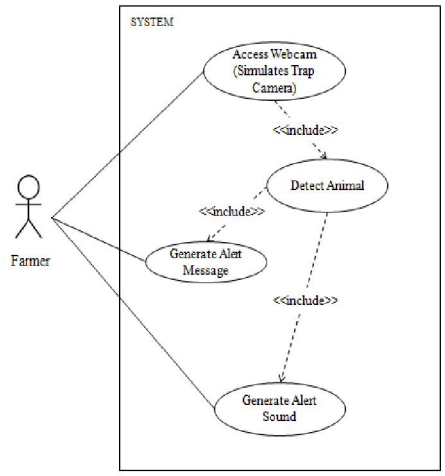

Figure 5: Usecase Diagram

B. Data Collection

Image data were collected from various wildlife species in controlled environments. The dataset was annotated and pre-processed for training. A Data Flow Diagram is the sequence of path data takes at it is generated on the system. It shows how data is processed if such data is valid and also specifies what happens when such data is invalid.

It uses defined symbols like rectangles, circles and arrows, plus short text labels, to show data inputs, outputs, storage points and the routes between each destination. Data flowcharts can range from simple, even hand-drawn process overviews, to in-depth, multi-level DFDs that dig progressively deeper into how the data is handled. They can be used to analyse an existing system or model a new one. Like all the best diagrams and charts, a DFD can often visually say things that would be hard to explain in words, and they work for both technical and nontechnical audiences.

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0^{th} Level

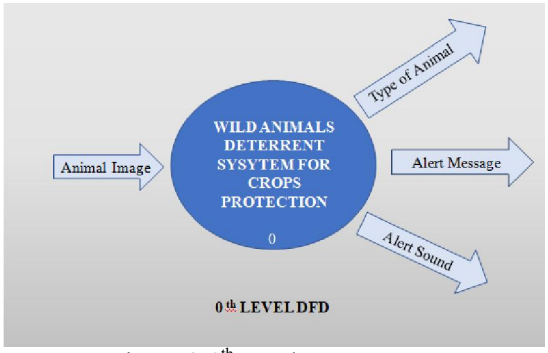

Figure 6: 0^{th} Level DFD

1^{st}Level

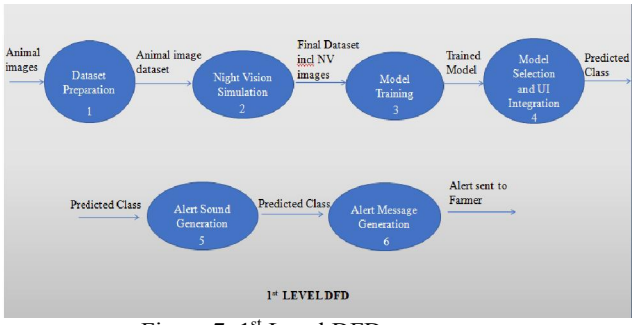

Figure 7: 1^{st} Level DFD

2^{nd} Level

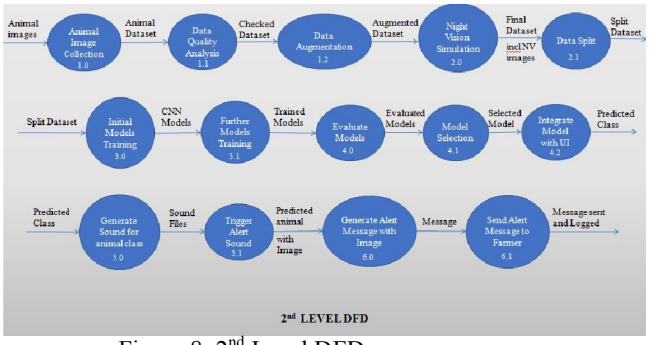

Figure 8: 2^{nd} Level DFD

C. Model Development

Dataset Preparation: Data quality analysis has to be done to ensure our dataset is well-suited for machine learning tasks. We began by visualizing samples from each class to gain an initial understanding of the dataset's structure. We then verified image integrity by checking for corrupted or empty images, preventing potential issues during training. Next, we assessed the dimensions of the images to ensure uniformity, identifying any inconsistencies. We also evaluated the resolution of the images, flagging those that did not meet our quality standards. Duplicate images were detected and removed by generating and comparing image hashes to eliminate redundancy. Finally, we analyzed class distribution to identify any imbalances in the dataset, ensuring a balanced representation of each class. Data augmentation further enhances the robustness and diversity of the dataset by generating additional samples per class through various image manipulation techniques. These techniques include rotation, flipping, brightness adjustment, Gaussian blur, and

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histogram equalization, among others. By augmenting the dataset with variations of existing images, we introduce diversity and complexity, enabling the model to learn from a broader range of scenarios and improve its generalization ability. Ultimately, the combination of data cleaning and augmentation techniques optimizes the quality, diversity, and size of the dataset, laying a solid foundation for effective model training and performance in tasks such as image classification and object detection.

Night Vision Simulation: Night vision simulation is a critical component in preparing image datasets for machine learning tasks, particularly in scenarios where low-light conditions may be encountered. Our approach to night vision simulation involves the application of various techniques to simulate the effect of night vision on input images, thereby enhancing the robustness and adaptability of our models to real-world conditions. These techniques include partial inversion, manual brightness adjustment, green tint application, noise addition, gamma correction, and vignetting. By incorporating these techniques, we aim to mimic the characteristics of night vision imagery, such as reduced visibility, altered color perception, and increased noise levels, ensuring that our models can effectively operate under challenging lighting conditions. Additionally, we have generated night vision images without a green tint to accommodate scenarios where black and white night vision simulation is desired, providing flexibility and versatility in our approach. Data splitting is a fundamental step in the machine learning pipeline, enabling the assessment of model performance and generalization ability. In our methodology, we divide the dataset into training, validation, and test sets to facilitate model training and evaluation. We leverage the scikit-learn 'train_test_split' function to partition images into their respective directories, ensuring a balanced distribution of classes across sets. By carefully splitting the dataset, we can train our models on a subset of the data, validate their performance on a separate subset, and ultimately evaluate their accuracy and robustness on a held-out test set. This systematic approach to data splitting enables reliable assessments of the model's performance and generalization ability in real-world scenarios.

D. Training and Evaluation

Effective model training and evaluation are pivotal for achieving high performance in deep learning applications. Our approach involved training a range of models using transfer learning to leverage pre-existing knowledge from large-scale datasets. Specifically, we fine-tuned VGG16, ResNet50, DenseNet121, EfficientNet (B0, B1, B2), Xception, InceptionV3, MobileNetV2, NASNetMobile, and NASNetLarge to our dataset. We began with basic versions of these models and assessed their performance based on accuracy and loss. The following table summarizes the performance metrics of the trained models:

Table 1: Model Training Result

Model	Loss	Accuracy
VGG16	44	87
ResNet50	48	87.7
DenseNet121	37	93
EfficientNetB0	23	93.4
EfficientNetB1	23	93.6
EfficientNetB2	19	94
Xception	22	93.8
Inception V3	30	91.8
MobileNet V2	52	87
NASNetMobile	39	91.6
NASNetLarge	24	95.8

We decided to focus on NASNetLarge, Xception, and EfficientNetB2 for subsequent fine-tuning based on their superior performance metrics, with each demonstrating high accuracy and relatively low loss in the initial evaluations. During this phase, we experimented with various hyperparameters, such as learning rates, optimizers, number of layers and epoch numbers, to optimize the models' performance. The objective was to enhance predictive accuracy and

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minimize loss further. The retraining process revealed that NASNetLarge consistently outperformed the other models, achieving an impressive final accuracy of 96% and a significantly reduced loss of 19%. These metrics were further validated using a hold-out test set to ensure robustness and reliability.

E. Model Selection and UI Integration

Model selection is a critical step in developing a high-performing deep learning system, as it involves identifying the model that best meets the performance criteria for a given task. We conducted a comprehensive evaluation using a hold-out test set to assess various performance metrics. These metrics included loss, accuracy, precision, recall, F1 score, and the confusion matrix. Loss and accuracy provided a fundamental measure of model performance. Precision, recall, and F1 score offered insights into the model's effectiveness in identifying and classifying instances correctly. The confusion matrix was used to visualize the model's performance across different classes, highlighting areas of strength and potential improvement. The NASNetLarge model demonstrated superior performance across these metrics, achieving high accuracy and low loss. Its high precision, recall, and F1 score further validated its effectiveness. The confusion matrix revealed minimal misclassifications, underscoring the model's reliability in accurately classifying the images. As a result, NASNetLarge was chosen as the final model, ensuring optimal performance and robustness for deployment in real-world scenarios.

F. Alert Sound and Message Generation

Sound generation and integration play a crucial role in our Wild Animals Deterrent System for Crop Protection, enhancing its effectiveness in deterring wildlife intrusion while minimizing harm to both animals and crops. To accomplish this, we first define animal classes along with their corresponding frequencies, ensuring that the generated sound stimuli are tailored to each specific species. We then implement a function using NumPy to generate sinusoidal waveforms with the specified frequencies and durations, enabling precise control over the characteristics of the generated sounds. These generated sound files are saved in WAV format for each animal class and stored in the 'animal sounds' directory, ensuring accessibility and ease of integration with the overall system architecture.

The integration of alert message generation and SMS notification functionalities within our Wild Animals Deterrent System for Crop Protection significantly enhances its ability to promptly inform farmers of potential wildlife intrusions, enabling timely response and intervention. Upon detecting an animal within the monitored area, the alert message generation module automatically creates a comprehensive notification containing crucial information such as the type of animal detected, timestamp of detection, and possibly an image of the detected animal for visual confirmation. Furthermore, the message can be customized to include additional details such as the precise location of the intrusion, sensor information, and any other relevant metadata, providing farmers with comprehensive insights into the incident.

IV. ALGORITHMS AND TECHNIQUES

A. NASNetLarge

The NASNetLarge model, short for Neural Architecture Search Network Large, represents a significant advancement in deep learning architecture, particularly in the realm of image classification. Developed by researchers at Google, NASNetLarge leverages a process known as Neural Architecture Search (NAS), which automates the design of neural networks. By employing NAS, the model can discover and construct optimal architectures that often outperform manually designed networks. This automation has led to the creation of a highly efficient and powerful model that has shown remarkable results in various image classification tasks, including our wildlife detection system.

NASNetLarge comprises a sophisticated and intricate architecture designed to maximize performance while maintaining computational efficiency. The core idea behind NASNetLarge is the use of a search space that defines possible neural network architectures, coupled with a reinforcement learning controller that explores this space to find the most effective configurations. This search space includes various building blocks, such as convolutional layers, pooling layers, and activation functions, which are combined in numerous ways to form different architectures.

The NASNetLarge model is built upon two primary components: Normal Cells and Reduction Cells. Normal Cells preserve the spatial dimensions of the input, performing standard convolutions and other operations to extract features. Reduction Cells, on the other hand, reduce the spatial dimensions, typically by a factor of two, allowing the network to

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increase its depth and capture more abstract features. These cells are stacked together in a repetitive manner, forming a deep and hierarchical structure that excels at learning complex patterns in images.

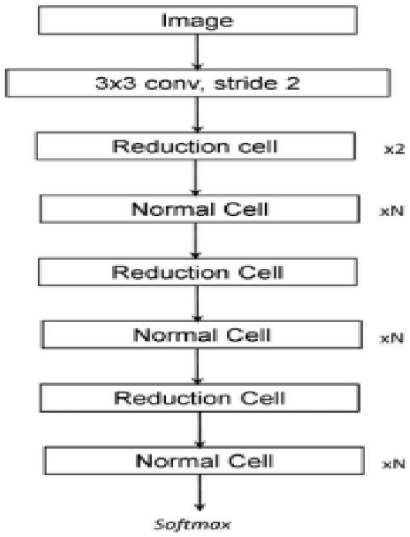

Figure 9: NASNetLarge Architecture

B. SGD Optimization

Stochastic Gradient Descent (SGD) is a fundamental optimization algorithm widely used in training machine learning models, particularly neural networks. It is popular due to its simplicity, efficiency, and effectiveness in minimizing the loss function by iteratively updating the model parameters.

The core idea behind SGD is to update the model parameters in the direction that minimizes the loss function, gradually converging towards the optimal solution. Unlike batch gradient descent, which computes the gradient of the loss function with respect to all training samples, SGD updates the parameters using a single randomly selected training sample or a small subset of samples (mini-batch) at each iteration. This stochastic sampling of training data introduces noise into the parameter updates, which helps the optimization process escape local minima and saddle points and enables faster convergence.

SGD iteratively updates the parameters using the computed gradient for a predefined number of iterations (epochs) or until convergence criteria are met. The learning rate is a critical hyperparameter in SGD, as it determines the step size of the parameter updates. Choosing an appropriate learning rate is essential to ensure stable convergence andprevent oscillations or divergence during training.

C. Cross-entropy Loss

Categorical Cross-Entropy Loss, also known as Softmax Cross-Entropy Loss, is a widely used loss function in machine learning, especially in classification tasks where the output belongs to multiple classes. Its primary function is to quantify the disparity between the true distribution of classes and the distribution predicted by the model.

The core concept of categorical cross-entropy loss revolves around measuring the difference between the actual probability distribution of classes and the distribution predicted by the model. Essentially, it penalizes the model for deviations from the true distribution, with more severe penalties incurred for larger discrepancies.

D. Reduce LRON Plateau

The ReduceLROnPlateau call back is another powerful tool used to optimize the learning rate during the training of deep learning models. Learning rate is a critical hyperparameter that influences how quickly a model converges to the optimal solution. If the learning rate is too high, the model might converge too quickly to a suboptimal solution.

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Conversely, a very low learning rate can make the training process excessively slow. ReduceLROnPlateau monitors a performance metric, such as validation loss, and reduces the learning rate when the metric stops improving. This adaptive adjustment ensures that the learning rate is optimal throughout the training process. In our project, implementing this call back helped in fine-tuning the model's parameters more effectively during the later stages of training, leading to improved model performance and stability. By reducing the learning rate when needed, the model was able to achieve higher accuracy and better generalization on the validation set.

V. EXPERIMENTAL RESULT

In our experimental setup, we utilized the NASNetLarge model for image classification with a custom architecture built upon its base. The final model was trained using a dataset of 6,516 images for training, 1,405 images for testing, and 1,397 images for validation, with a data split ratio of 7:1.5:1.5. The image data was preprocessed using a rescaling factor of 1/255, and a batch size of 16 was employed during training. The model architecture included global max pooling, dropout for regularization, and fully connected dense layers, concluding with a softmax output layer for multiclass classification. Training was executed with early stopping, reducing learning rate on plateau, and model checkpoint callbacks to optimize performance and prevent overfitting. The optimizer used was SGD with a learning rate of 0.01, and categorical cross-entropy was employed as the loss function. The model's performance metrics were evaluated on the hold-out validation set. The final model achieved an impressive accuracy of 96% with a loss of 19%, demonstrating its robustness in classifying the 13 distinct classes present in the dataset.

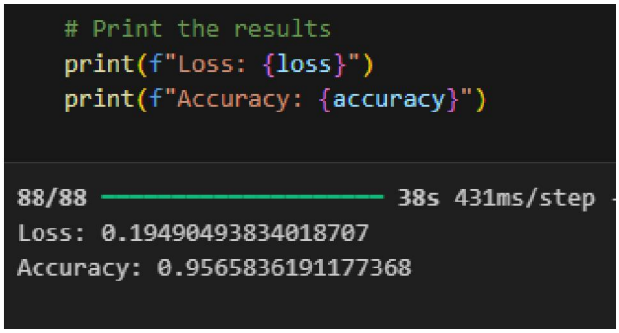

Figure 10: Experimental Result

A. Precision

Precision is defined as the ratio of correctly classified positive samples (True Positive) to a total number of classified positive samples (either correctly or incorrectly 1).

Precision=True Positive/True Positive + False

Positive Precision = TP/TP+FP

- TP-True Positive
- FP-False Positive
- The precision of a machine learning model will below when the value of;
- TP+FP(denominator)>TP(Numerator)
- The precision of the machine learning model will be high when Value of;
- TP(Numerator)>TP+FP(denominator)

B. Recall

Recall, also known as the true positive rate(TPR), is the percentage of data samples that a machine learning model correctly identifies as belonging to a class of interest—the ―positive class‖—out of the total samples for that class.

Recall formula= True Positives in all classes / (True Positives + False Negatives in all classes)

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C. Recall vs Precision

For imbalanced classification problem recall and precision are both better-suited metrics than simply relying only on the accuracy of a model. However, that doesn‘t mean they are equally important. In a specific situation, you may want to maximize either recall or precision at the cost of the other metric. You can‘t have both, high recall and high precision, so there is a certain cost in getting higher points for either of them. In some cases, you want to take both metrics into account and find an optimal blend by using the F1 score.

F1=2*(precision*recall/(precision + recall))

The F1 score is defined as the harmonicmean of precision and recall. As a short reminder, theharmonicmeanis an alternative metric for the more common arithmetic mean. It is often useful when computing an average rate.In the F1 score, we compute theaverage of precision and recall. They are both rates, which makes it a logical choice to use the harmonic mean. The F1 score formula is shown here:

F1 score =2*(precision*recall/(precision + recall))

Classification Report:

	precision	recall	f1-score	support
0	0.98	0.97	0.98	102
1	0.98	0.98	0.98	111
2	0.90	0.97	0.93	103
3	0.94	0.90	0.92	105
4	0.96	0.97	0.96	123
5	0.95	0.94	0.95	102
6	0.95	0.95	0.95	109
7	0.98	0.95	0.97	107
8	0.94	0.97	0.96	101
9	0.98	0.96	0.97	134
10	0.99	0.96	0.97	99
11	0.97	0.95	0.96	103
12	0.92	0.96	0.94	106
accuracy			0.96	1405
macro avg	0.96	0.96	0.96	1405
weighted avg	0.96	0.96	0.96	1405

Figure 11: Precision, Recall, F1 Score

D. Confusion Matrix

The confusion matrix is a matrix used to determine the performance of the classification models for a given set of test data. It can onlybe determined if the true values for test data are known. The matrix itself can be easily understood, but the related terminologies may be confusing. Since it shows the errors in the model performance in the form of a matrix, it is also known asan error matrix.

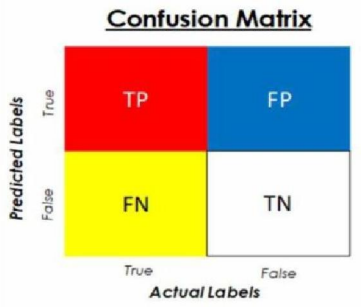

Figure 12: Confusion Matrix

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E. Output

Initializing login with user credentials

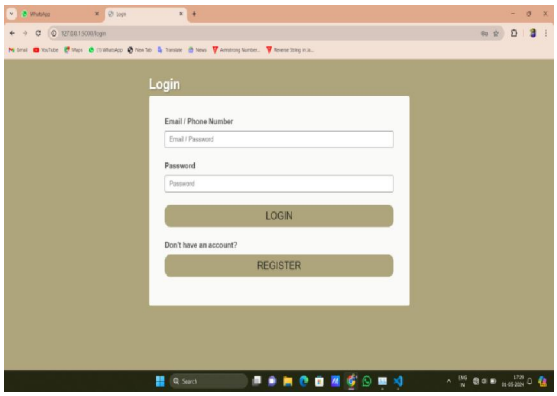

Figure 13: Login Page

Animal Detection UI Screen with sampling images

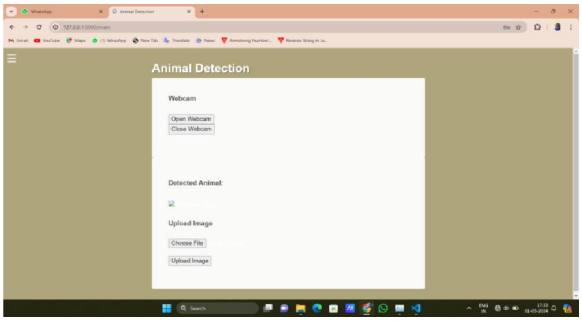

Figure 14: Prefeed the detection screen

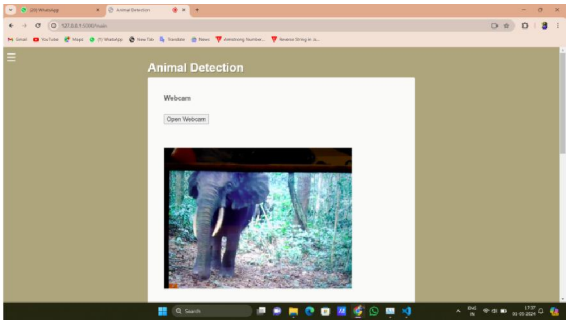

Figure 15: Output 1

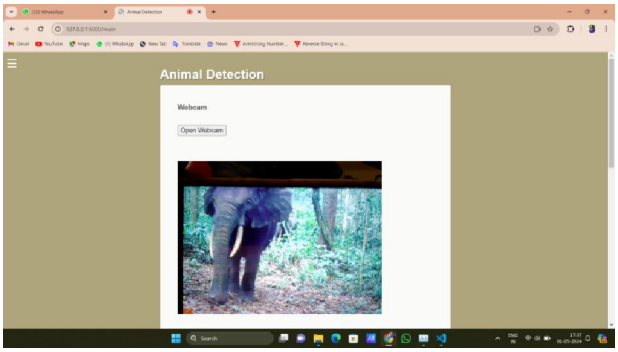

Figure 16: Output 2

IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
Impact Factor: 7.67
Volume 5, Issue 7, March 2025

CONCLUSION

In conclusion, the development and implementation of the Wild Animals Deterrent System for Crop Protection represent a significant step forward in addressing the challenges posed by wildlife intrusion in agricultural settings. Through the integration of advanced technologies such as deep learning-based animal detection, sound generation, and alert notification systems, our solution offers a comprehensive and effective approach to safeguarding crops while minimizing harm to wildlife. By leveraging techniques such as transfer learning, data augmentation, and night vision simulation, we have demonstrated the potential for enhanced accuracy and robustness in detecting and repelling wild animals.

While our project represents a significant advancement in crop protection technology, there are several avenues for future research and development to further enhance its efficacy and versatility. One potential direction is the exploration of additional sensor modalities, such as infrared imaging or acoustic sensors, to augment the detection capabilities of the system and improve its performance under diverse environmental conditions. Furthermore, incorporating advanced machine learning techniques, such as reinforcement learning or ensemble methods, could enable the system to adapt and optimize its strategies dynamically based on evolving environmental factors and wildlife behaviors. Additionally, extending the functionality of the system to include predictive analytics and decision support tools could empower farmers with actionable insights. Overall, continued innovation and collaboration in this field hold the promise of delivering more sophisticated and sustainable solutions for crop protection and wildlife management in agricultural landscapes.

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IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
Impact Factor: 7.67
Volume 5, Issue 7, March 2025

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