ANIMAL INTRUSION DETECTION MODEL BASED ON TEMPORAL CONVOLUTION NETWORK FOR SMART FARMING

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ABSTRACT

Human-wildlife conflicts, spurred by habitat encroachment and deforestation, result in substantial crop raiding, endangering farmers and human safety. Traditional mitigation methods, costly and environmentally damaging, lack effectiveness. Our solution, the Integrated Wildlife Management System, merges Computer Vision with Temporal Convolutional Networks for precise species detection and ultrasound emission for species-specific repelling. Triggered by an edge computing device, a camera activates an Animal Intrusion Detection Model to identify invading species, initiating the emission of species-specific ultrasound by the Animal Repelling Module upon detection. This system offers a robust solution for safeguarding crops from diverse wild animals like elephants, wild boar, and deer. Through technological innovation, we aim to balance crop protection and environmental preservation, contributing to discussions on human-wildlife conflict resolution..

Keywords—Temporal Convolution Network ,Computer Vision ,Intrusion Detection ,Animal repelling

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Agriculture has undergone numerous revolutions, from ancient domestication to modern practices like crop rotation and the "green revolution." Now, a fourth revolution is underway, driven by the integration of information and communication technology (ICT). This includes autonomous robotic vehicles for tasks like weeding and harvesting, unmanned aerial vehicles with hyperspectral cameras for crop monitoring, and decision-tree models for diagnosing plant diseases. Virtual fence technologies facilitate remote cattle herd management. These advancements will revolutionize agriculture globally, benefiting both developed and developing countries. The increasing adoption of ICT, especially mobile phones and internet access, in developing nations promises significant changes, such as improved seasonal forecasting and climate-smart techniques. In essence, these innovations represent a disruptive force reshaping agriculture worldwide.

I. LITERATURE SURVEY

Workflow and convolutional neural network for automated identification of animal sounds
Authors: Zachary J.Ruff, Damon B.Lesmeister, Cara L.Appel, Christopher M.Sullivan
Year: 2021
Link: https://www.sciencedirect.com/science/article/pii/S1470160X21000844
Objective:
The aim of this project is automated identification of animal sounds using Convolutional Neural Networks.
Methodology:

Passive acoustic monitoring in wildlife ecology has seen a significant rise in recent years, leveraging advancements in autonomous recording units and analytical techniques. These innovations enable the collection of extensive acoustic data, which requires processing to derive meaningful insights, such as identifying target species. One ongoing challenge in acoustic monitoring is efficiently automating species detection, a task where deep learning has proven highly effective. This article presents the development and deployment of a deep convolutional neural network to automatically detect 14 forest-adapted birds and mammals by analyzing spectrogram images derived from brief audio clips. It introduces a multi-step workflow that *seamlessly incorporates this neural network, streamlining the processing of large audio datasets through a blend of automated detection and human review. This approach drastically reduces human workload by more than 99% compared to manual data review. Additionally, the article suggests an optional graphical interface for the neural network, accessible via RStudio using the Shiny package. This feature offers field biologists and managers a portable, user-friendly tool to process audio data efficiently, enabling near-real-time species detection at the collection site using standard computers.*

Figure 2.1. Steps involved in audio processing and target species detection workflow.
Merits:
Accuracy is high.
Minimal delays using consumer-grade computers.
Its Efficiency is high.
Demerits:
High power to detect these species.
Combined with a low proportion of false positives.

Real-Time Monitoring of Agricultural Land with Crop Prediction and Animal Intrusion Prevention using Internet of Things and Machine Learning at Edge
Authors: R. Nikhil; B.S. Anisha; Ramakanth Kumar P.
Year: 2020
Link: https://ieeexplore.ieee.org/document/9198508
Objective:
The aim of this project is crop prediction helps the farmers to grow suitable crops depending on the soil parameters by the use of machine learning techniques and it also helps in prevention of the intruders like wild animals into the field.
Methodology:
The smart agriculture system implemented prioritizes cost-effectiveness to optimize farm water supplies, predict crops, and prevent wild animal intrusion. It operates by adjusting water sprinklers based on soil moisture levels, simplifying the irrigation process. Additionally, it forecasts crops according to soil conditions, aiding farmers in cultivating appropriate crops at optimal times. Utilizing IoT and automation, the system significantly advances irrigation practices. Furthermore, it deters wild animals from trespassing into agricultural areas using ultrasonic sound to irritate and repel them, employing eco-friendly alarm tone flooding techniques with minimal energy consumption. While the system promotes ecosystem preservation and human safety, it currently faces challenges related to monitoring and accuracy.Merits:
There is no harm to the ecosystem.
No disruption to humans.
Using the alarm tone flooding techniques which requires less energy.
Demerits:
Lacks in monitoring.
Accuracy is low.

Animal Behaviour Prediction with Long Short-Term Memory
Authors: Henry Roberts; Aviv Segev
Year: 2020
Link: https://ieeexplore.ieee.org/document/9378184
Objective:
The aim of this project is efficiently converting video of animals at any length into models capable of making accurate behavioural prediction using Long Short-term Memory (LSTM).
Methodology:
Establishing an accurate behavioral model is a fundamental aspect of studying any animal. Constructing a model capable of defining and forecasting animal behavior is crucial for advancing ethological research, yet many existing models lack thoroughness or do not exist altogether. Despite vast amounts of data available from videos of animals on internet hosting platforms, researchers often overlook these sources due to the overwhelming volume of data, making manual observation and annotation impractical. This article proposes a pipeline approach to efficiently develop predictive behavioral models by leveraging various machine learning tools. It compares the accuracy and significance of predictions against a traditional time-series analysis statistical model. Results from testing this proposed pipeline indicate promising outcomes, as the LSTM network trained on JAABA annotated frames and classifier function results demonstrates superior performance compared to the ARIMA model.
Merits:
Its prediction applied to large datasets and yield useful results.
Model's accuracy in prediction
Demerits:
Time-series analysis statistical model is high.

Its efficiency is low.

II. PROBLEM STATEMENT

Farmers face significant challenges with crop damage from wildlife and domestic animals, impacting food security and profits. Animal intrusion manifests through tracks, crop damage, and faecal matter, each posing varying risks. While sporadic tracks suggest moderate risk, widespread evidence demands action like creating buffer zones. Crop damage, from bite marks to trampled plants, indicates higher risk, necessitating strategic harvest avoidance. Faecal matter presents the highest risk, with even one instance demanding caution and widespread evidence warranting buffer zones.

Traditional methods like fencing are limited, prompting the exploration of smarter solutions. Utilizing technology such as IoT and Deep Learning, termed AIoT, offers promise in mitigating wildlife intrusion without harming animals. This approach seeks to protect crops effectively while promoting coexistence between agriculture and wildlife, addressing the shortcomings of conventional methods.

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III. METHODOLOGY

Our proposed methodology included data Collection, pre-processing and deciding algorithms, training and result analysis.

Data Collection:

Animals (Object) Detection dataset extracted using Google Open Images V6+. It contains about 700 medium quality animal images belonging to 7 categories: goat, pig, bear, sheep, cow, elephant, horse. Each class has a maximum of 120 images, with some classes having only 60 images. I resized every image to 224x224 to save on space.These datasets are annotated.

Fig (a): Collected image samples

Capturing Live Frame:

The live monitoring of the fields allows us to detect the presence of any domestic or wild animal.We can also use pre-recorded videos for monitoring.

Pre-processing:

We pre-process the images by RGB to grey scale conversion, Resizing the images, Removing any noise, Binarization, Segmentation in order to remove any impurities or noise in the dataset..

Architecture:

Temporal Convolutional Networks (TCNs) are a type of neural network architecture specifically designed for processing sequential data, such as time series or temporal sequences. Unlike traditional convolutional neural networks (CNNs) which are primarily used for processing spatial data like images, TCNs are tailored to capture patterns and dependencies across time.This is trained to detect and recognize various types of animals. This involves learning features and patterns from input data to make accurate predictions. The system outputs predictions regarding the presence of animals providing information such as type of animal detected and confidence score. Along with detecting animals the system detects the specific type of animals.

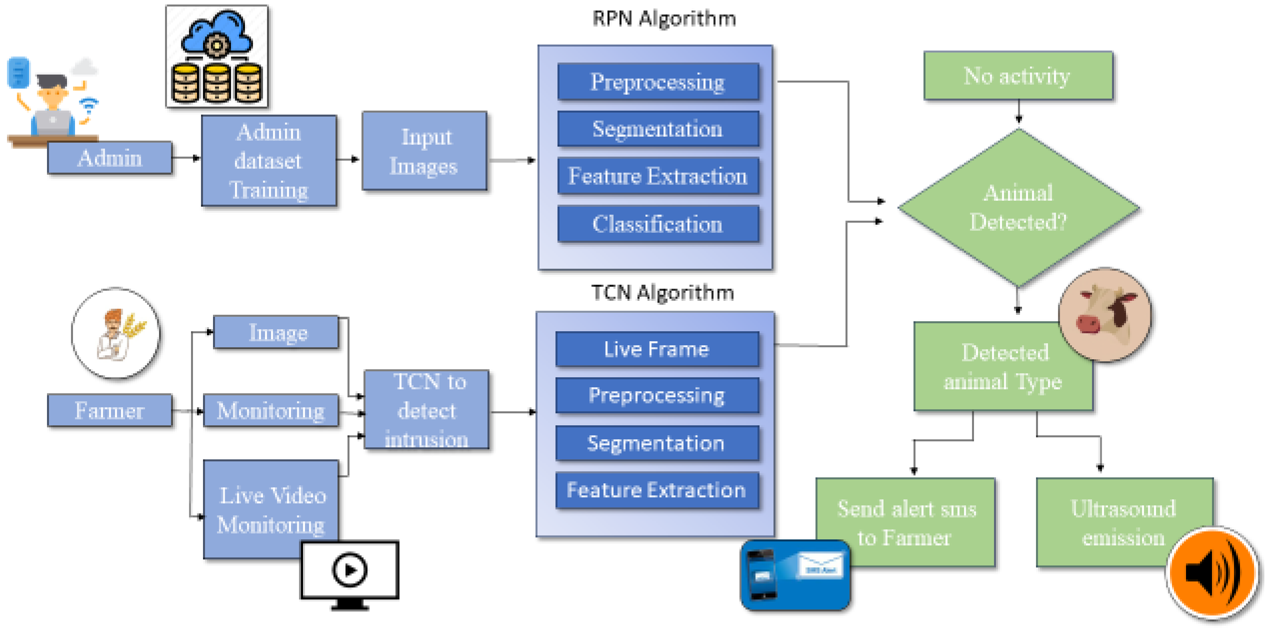

Fig (b): Architecture

Accuracy and precision of the Model:

The accuracy and precision of the model is displayed below.

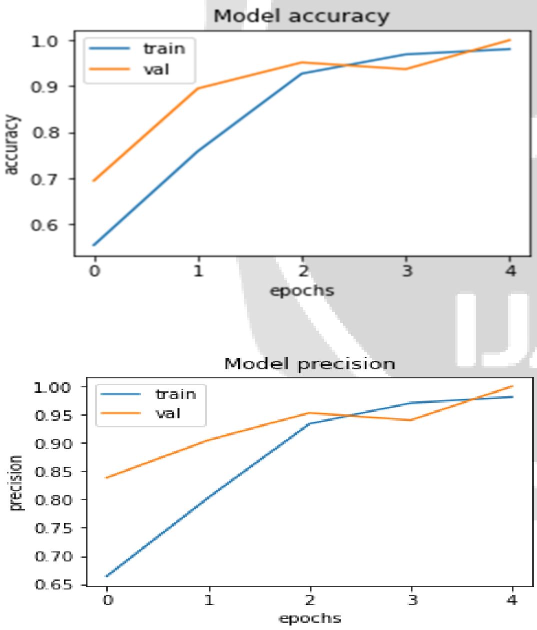

Fig (c): Models with accuracy and precision

Training:

In this training phase we need to decide number of epochs and batch size to train the model to gain accuracy in object detection.

Testing:

Testing the model with testing images and validating whether the model detects the images correctly.

Fig (d): Validating and testing images

Result Analysis:

The result analysis shows the number of correctly detected label in confusion matrix. F1 Curve shows the confidence level of each classes. Correlogram shows the number of correlated classes. R1 curve shows the recall confidence level.

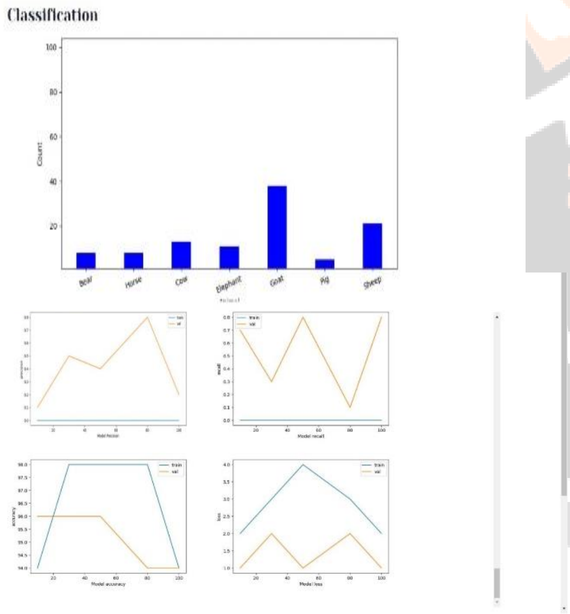

Fig (f): Training and object loss

IV. Dataset or Experimental Setup

Dataset enclosed of numerous amount of images of animals. There are almost 5000 images with 2, 00,000 anchor points. In this experimental setup, the deep learning algorithms find the valuable insight to get the anchor points. The images are resized into size(360,480,3).

V. Result

The trained model shows the most accurate result in object detection with Accuracy: 0.9984025559105432,Precision:

0. 9990234375,Recall: 0.9964285714285714,F1_score: 0.9977122020583142 scores.

Fig (g): Testing with real time images.

CONCLUSION

An agricultural farm security system has been developed using Python and OpenCV, employing a vision-based approach for real-time animal detection and repellence. This system integrates intelligent animal repulsion capabilities to prevent crop damage caused by animals. Upon detection of an animal, the edge computing device utilizes a Temporal Convolutional Network (TCN) Animal Recognition model to identify the species and triggers the Animal Repelling Module accordingly. Experimental evaluation of the TCN on a diverse animal database demonstrates excellent recognition rates, reaching up to 98% accuracy with increased training data. This real-time monitoring solution based on AI technology offers farmers and agronomists an effective tool for decision-making and crop management, addressing the persistent challenge of animal-related crop damages.

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