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Animal Intrusion Detection Model based on Temporal Convolutional Network for Smart Farming

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ABSTRACT: Human-wildlife conflicts arising from habitat encroachment and deforestation have led to an alarming increase in crop raiding, causing substantial losses to farmers and posing risks to human safety. Conventional methods, ranging from lethal measures to non-lethal deterrents, have proven insufficient, often leading to environmental pollution, high costs, and limited effectiveness. In response to these challenges, this project proposes novel Integrated Wildlife Management System that combines Computer Vision, leveraging Temporal Convolutional Networks (TCN), for precise animal species detection and recognition, with a targeted ultrasound emission technique for species-specific repelling. This model accurately identifies the invading species, and upon detection, transmits a message to the Animal Repelling Module. In response, the module emits a species-specific ultrasound, effectively deterring the encroaching wildlife. Distinguishing itself from traditional methods, our approach minimizes environmental pollution and addresses financial constraints associated with maintenance costs and reliability issues. This project contributes to the ongoing discourse on human-wildlife conflict resolution and highlights the potential of technology-driven solutions in fostering coexistence between agriculture and biodiversity.

I. INTRODUCTION

Agriculture has seen many revolutions, whether the domestication of animals and plants a few thousand years ago, the systematic use of crop rotations and other improvements in farming practice a few hundred years ago, or the “green revolution” with systematic breeding and the widespread use of man-made fertilizers and pesticides a few decades ago. Agriculture is undergoing a fourth revolution triggered by the exponentially increasing use of information and communication technology (ICT) in agriculture. Autonomous, robotic vehicles have been developed for farming purposes, such as mechanical weeding, application of fertilizer, or harvesting of fruits. The development of unmanned aerial vehicles with autonomous flight control, together with the development of lightweight and powerful hyperspectral snapshot cameras that can be used to calculate biomass development and fertilization status of crops, opens the field for sophisticated farm management advice. Moreover, decision-tree models are available now that allow farmers to differentiate between plant diseases based on optical information. Virtual fence technologies allow cattle herd management based on remote-sensing signals and sensors or actuators attached to the livestock. Taken together, these technical improvements constitute a technical revolution that will generate disruptive changes in agricultural practices.

II. EXISTING SYSTEM

Traditionally, farmers have employed various methods to repel animals from their crops and livestock. While these methods may lack the sophistication of modern AI-based systems, they have been effective in certain contexts. Erecting physical barriers like fences and walls is a common method to prevent animals from entering crop fields. These barriers act as a deterrent and provide a visible boundary. Farmers often use chemical repellents sprayed on crops to deter animals. These can include substances with strong odours or tastes that animals find unpleasant. Scarecrows have been a traditional method of deterring birds. They are human-like figures placed in fields to create the illusion of a human presence, scaring away birds. Hare Cascade is a machine learning object detection algorithm that uses a set of positive and negative images to train a classifier.

III. LITERATURE SURVEY

Most farmers have challenges related to crop damage due to wildlife pests. Animal intrusion is a major threat to the productivity of the crops, which affects food security and reduces the profit to the farmers. Organic farmers have

additional challenges because they cannot use chemical controls which are sometimes the most effective and efficient options. A need has been identified for alternative pest control appropriate for traditional and organic farmers. Three types of animal intrusion you might find include animal tracks, crop damage and animal scat or faeces. In the case of animal tracks, only one instance of tracks in the field carries a relatively low risk. On the other hand, sporadic or widespread animal tracks carry a moderate risk, and a no-harvest buffer zone may need to be created around nearby crops. Crop damage, such as bite marks or trampled plants, is riskier than animal tracks. Sporadic evidence, such as a few observations of trampled plants throughout the field, is moderately risky.

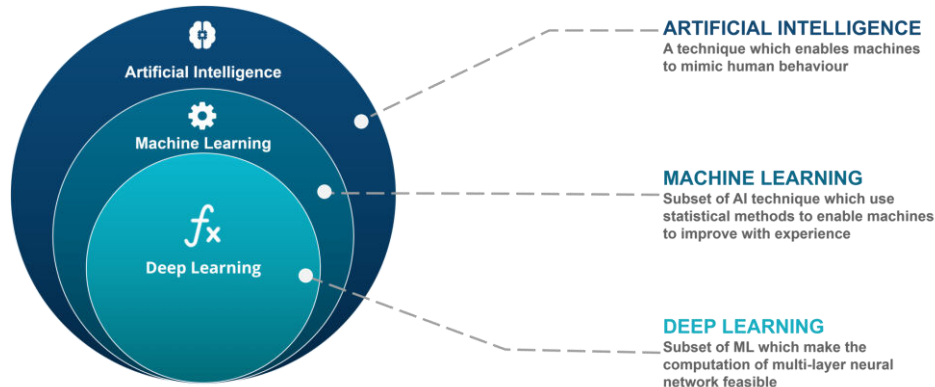


Fig 1: Artificial Intelligence

An AI is a computer system that is able to perform tasks that ordinarily require human intelligence. These artificial intelligence systems are powered by machine learning. Many of them are powered by machine learning, some of them are powered by specifically deep learning, some of them are powered by very boring things like just rules.

Machine learning allows experts to “train” a machine by making it analyze massive datasets. The more data the machine analyzes, the more accurate results it can produce by making decisions and predictions for unseen events or scenarios. Machine learning models need structured data to make accurate predictions and decisions.

IV. PROPOSED SYSTEM

This project presents an integrated system aimed at addressing wildlife-related challenges in agriculture by combining advanced AI technologies with targeted ultrasound emissions and farmer alert mechanisms. The system utilizes Temporal Convolutional Network (TCN) and WildNet for accurate detection and recognition of animal species, coupled with species-specific ultrasound emissions for repelling identified animals. Additionally, the system incorporates an alert system to notify farmers via SMS when potential threats are detected. The TCN and Wild Net form the core of the computer vision module, offering real-time video analysis for accurate detection and recognition of animal species.

CONVOLUTIONAL NEURAL NETWORK – Wild Net Model

A Convolutional Neural Network (ConvNet/CNN) is a Deep Learning algorithm that can take in an input image, assign importance (learnable weights and biases) to various aspects/objects in the image, and be able to differentiate one from the other. The pre-processing required in a ConvNet is much lower as compared to other classification algorithms. While in primitive methods filters are hand-engineered, with enough training, ConvNets have the ability to learn these filters/characteristics. The architecture of a ConvNet is analogous to that of the connectivity pattern of Neurons in the Human Brain and was inspired by the organization of the Visual Cortex. Individual neurons respond to stimuli only in a restricted region of the visual field known as the Receptive Field. A collection of such fields overlap to cover the entire visual area.

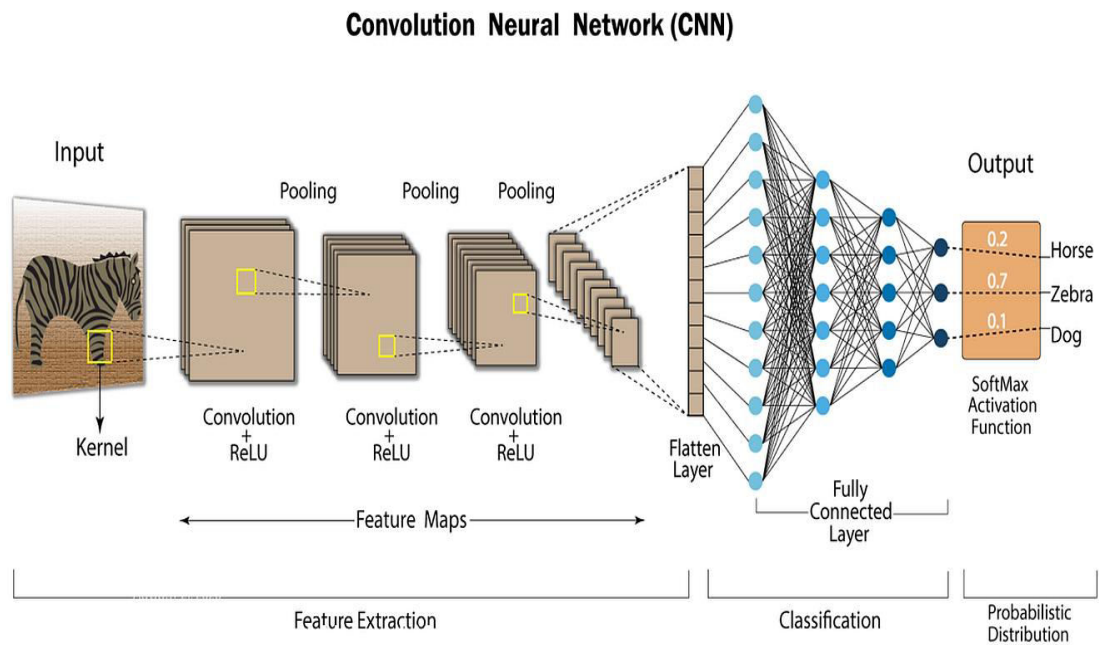


Fig 2: Convolution neural network

Convolutional Layer + Relu

This layer is the first layer that is used to extract the various features from the input images. In this layer, the mathematical operation of convolution is performed between the input image and a filter of a particular size $M \times M$. By sliding the filter over the input image, the dot product is taken between the filter and the parts of the input image with respect to the size of the filter ($M \times M$). The output is termed as the Feature map which gives us information about the image such as the corners and edges. Later, this feature map is fed to other layers to learn several other features of the input image.

TEMPORAL CONVOLUTIONAL NETWORKS

The seminal work of Lea et al. (2016) first proposed a Temporal Convolutional Networks (TCNs) for video-based action segmentation. The two steps of this conventional process include: firstly, computing of low-level features using (usually) CNN that encode spatial-temporal information and secondly, input these low-level features into a classifier that captures high-level temporal information using (usually) RNN. The main disadvantage of such an approach is that it requires two separate models. TCN provides a unified approach to capture all two levels of information hierarchically.

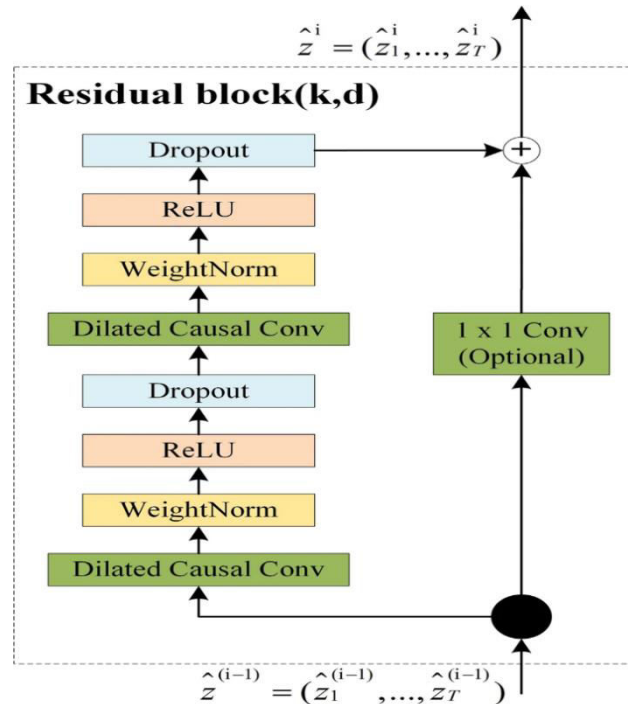


Fig 3: Temporal convolutional networks

TCN model has two layers, i.e., a dilated causal convolution and non-linearity (ReLU), as well as weight normalization in between. In addition, a spatial dropout was added after each dilated convolution for regularization, and an additional 1×1 convolution was adopted to ensure that the element-wise addition \oplus received tensors of the same shape to resolve the difference in input and output widths. The typical characteristics of TCN includes: (1) It can take a sequence of any length and output it as a sequence of the same length with the input, just like using an RNN; and (2) the convolution is a causal convolution, which means that there is no information “leakage” from future to past. To reach the first goal, the TCN uses a one-dimensional, fully convolutional network (1D FCN) architecture⁴⁶. That is, each hidden layer will be padded zero to maintain the same length with the input layer. To achieve the second point, the causal convolution, where an output at time t is convolved only with elements from time t and earlier in the previous layer, is adopted. In short, TCN is the sum of 1D FCN and causal convolutions.

WEB APP FOR ANIMAL INTRUSION

Admins securely access the system through a dedicated login page, ensuring authentication and authorized entry. Various mechanisms such as username-password combinations ensure a secure login process. Admins can effortlessly upload diverse datasets of labelled wildlife images for the WildNet model training. The system supports multiple image formats and ensures proper labelling for accurate model learning, contributing to enhanced species recognition. In a dedicated section, admins initiate and monitor the training of WildNet models. Parameters such as epochs, learning rates, and model architectures are configurable, allowing for precise customization and optimization during the training process. Following successful training, admins deploy the trained WildNet model to edge devices. The deployment process is carefully validated, ensuring compatibility with target devices and efficient integration into the wildlife defence system. Admins associate ultrasound emissions with specific wildlife species through a user-friendly interface. This functionality allows for the customization and configuration of ultrasound repellents corresponding to each trained model, promoting targeted and humane wildlife deterrence.

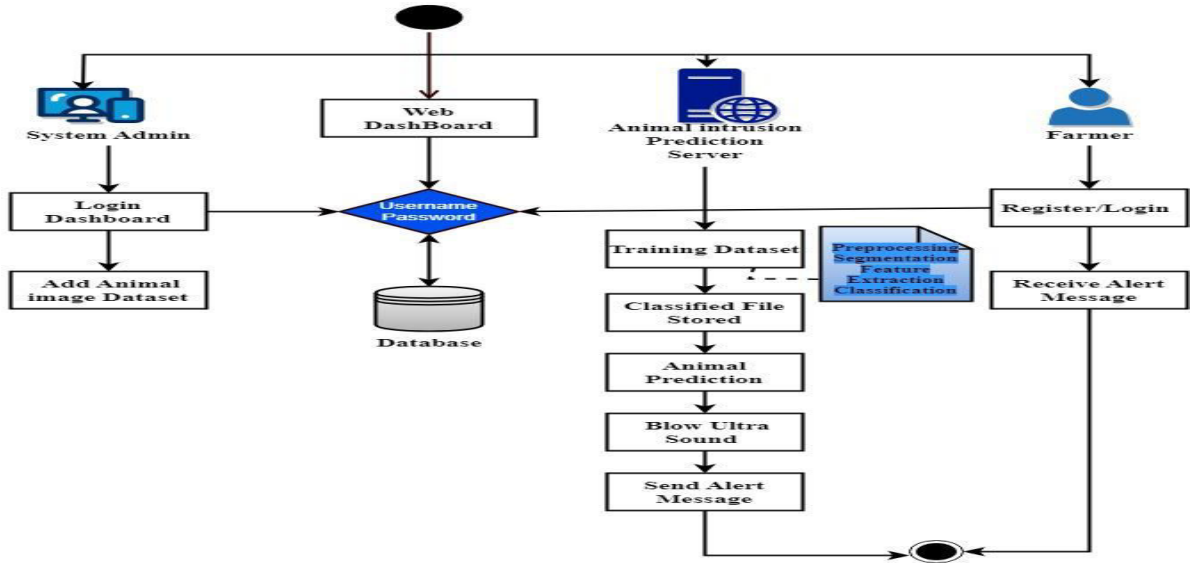


Fig 4: Flowchart

Farmers initiate their engagement with the system by registering and providing essential details such as name, contact information, and farm location. The registration process includes verification mechanisms, enhancing data accuracy and system security. Authenticated farmers gain access to their accounts using secure credentials, ensuring a private and secure login experience tailored to individual farmer profiles. Farmers access a real-time monitoring dashboard presenting live camera feeds from their fields. The dashboard provides valuable insights, including intrusion alerts, deployed WildNet model status, and ultrasound activation information, empowering farmers with immediate visibility into their farm activities. Farmers can access detailed reports on wildlife intrusion incidents, offering insights into intrusion patterns, species identification, and the effectiveness of deployed countermeasures. The reports support informed decision-making for effective wildlife management. In situations requiring immediate action, farmers utilize manual controls available through the interface, including the activation of buzzers or other deterrent measures. This feature empowers farmers to respond promptly to potential threats, enhancing the system's proactive defence capabilities.

V. RESULT

SCREENSHOT

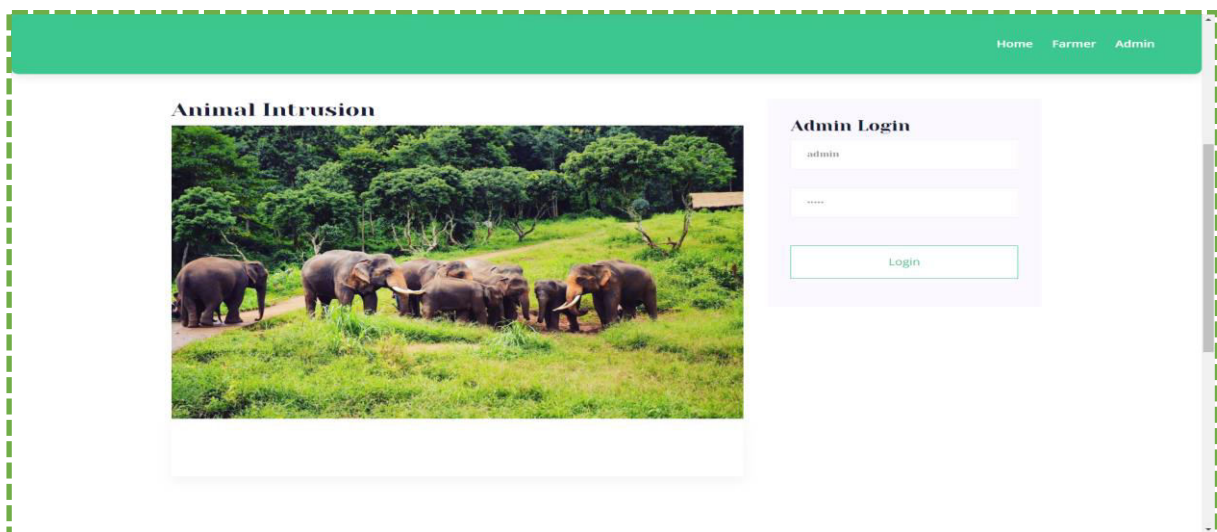


Fig 5: Admin Login

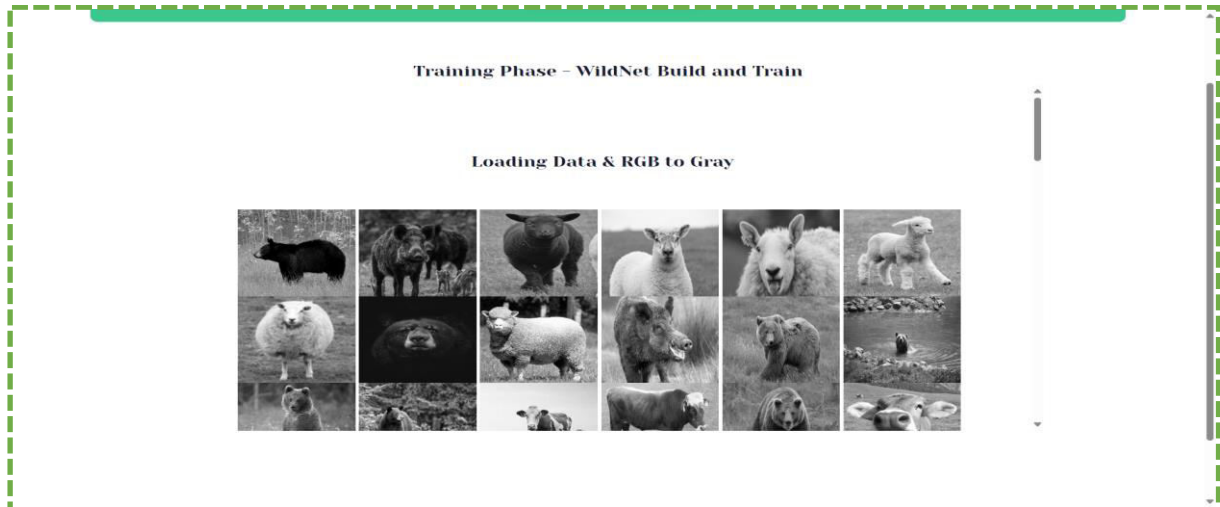


Fig 6: Wild-net Build and Train

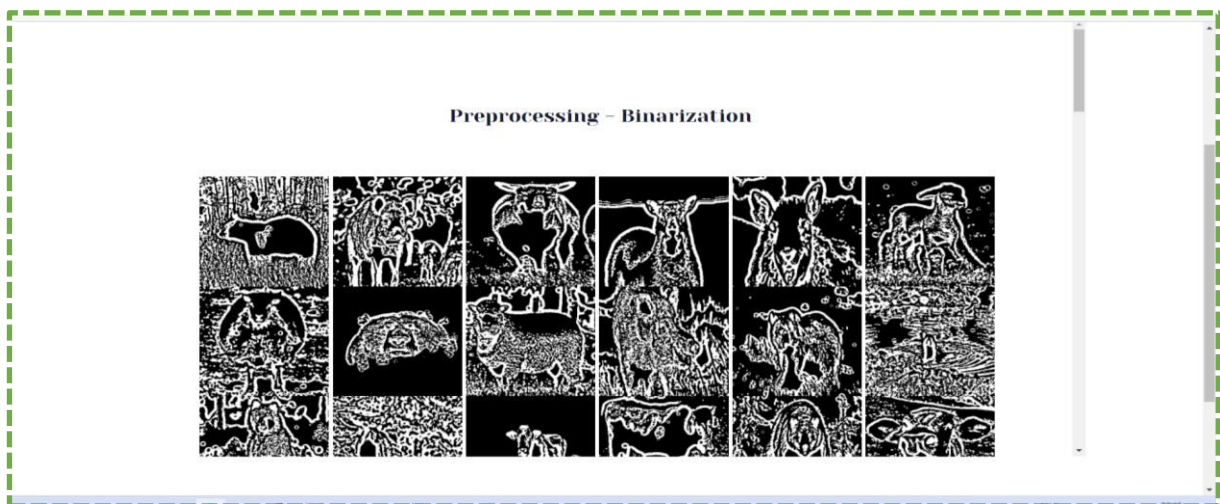


Fig 7: Pre-processing Binarization

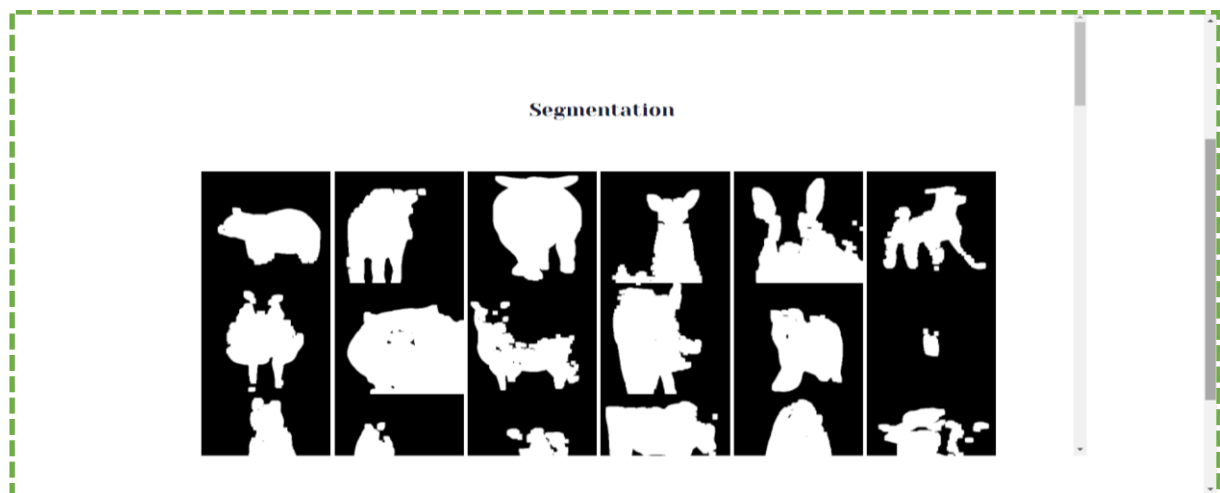


Fig 8: Segmentation

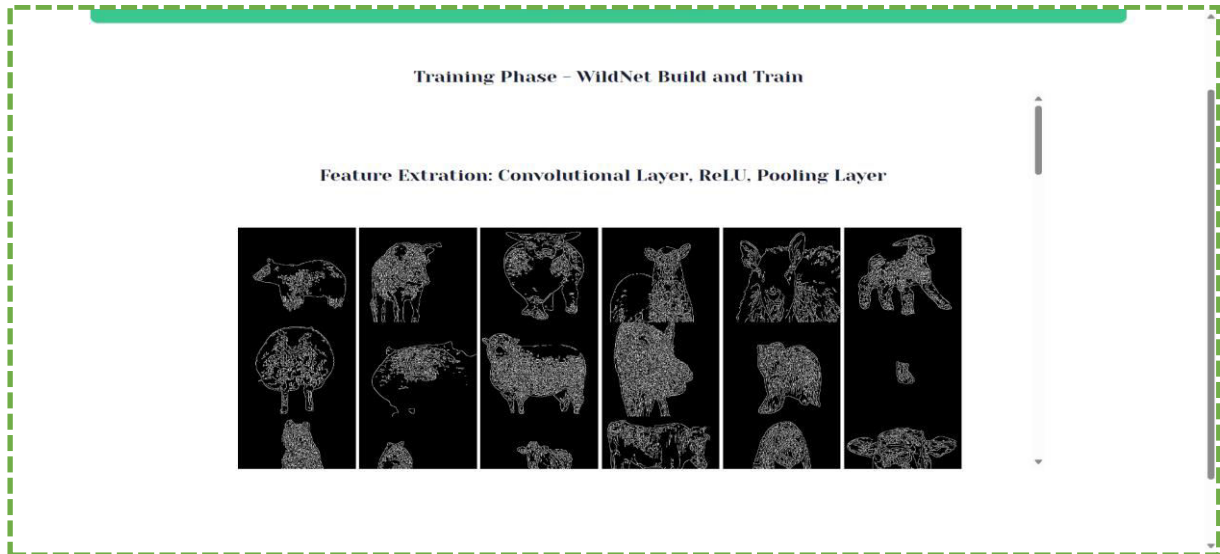


Fig 9: Convolutional Layer,ReLU:Pooling Layer

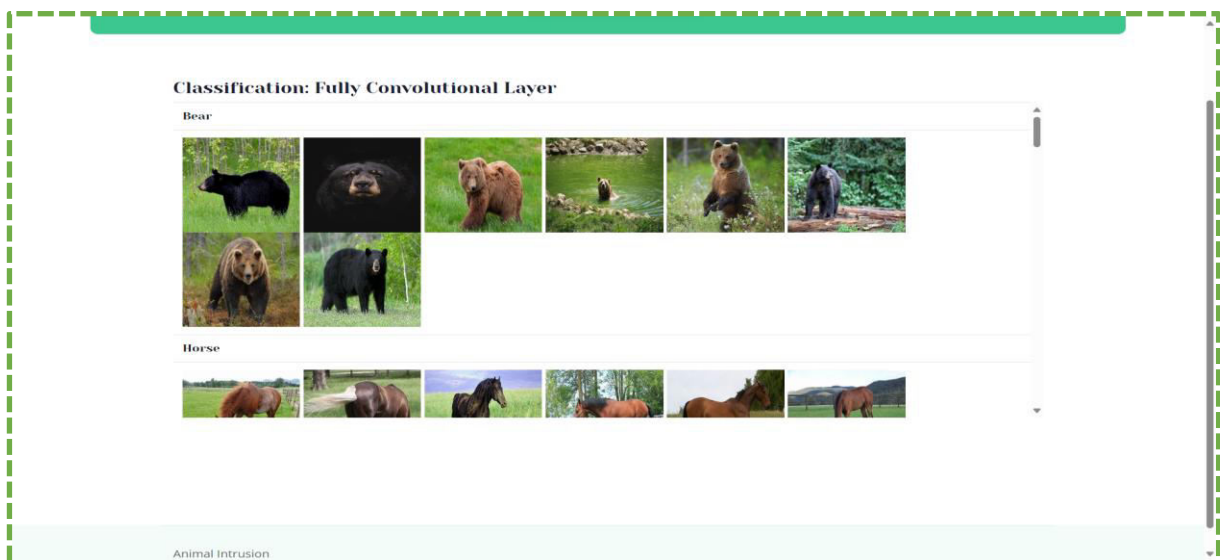


Fig 10: Classification: Fully Convolutional Layer

OUTCOME: The development of an animal intrusion detection model based on Temporal Convolutional Networks (TCNs) for smart farming has shown promising outcomes. By leveraging the ability of TCNs to capture temporal dependencies in sequential data, this model effectively identifies patterns associated with animal movements, thereby distinguishing between normal farm activities and potential intrusions. The high accuracy and real-time detection capabilities of this model enhance farm security and reduce crop damage and livestock threats. Furthermore, its implementation in smart farming systems promotes the efficient management of resources, leading to increased productivity and sustainability in agricultural practices.

VI. CONCLUSION

Agricultural farm security is widely needed technology nowadays. In order to accomplish this, a vision-based system is proposed and implemented using Python and OpenCV and developed an Animal Repellent System to blow out the animals. The implementation of the application required the design and development of a complex system for intelligent animal repulsion, which integrates newly developed software components and allows to recognize the presence and species of animals in real time and also to avoid crop damages caused by the animals. the edge



computing device executes its TCN Animal Recognition model to identify the target it sends back a message to the Animal Repelling Module including the type of ultrasound to be generated according to the category of the animal.

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