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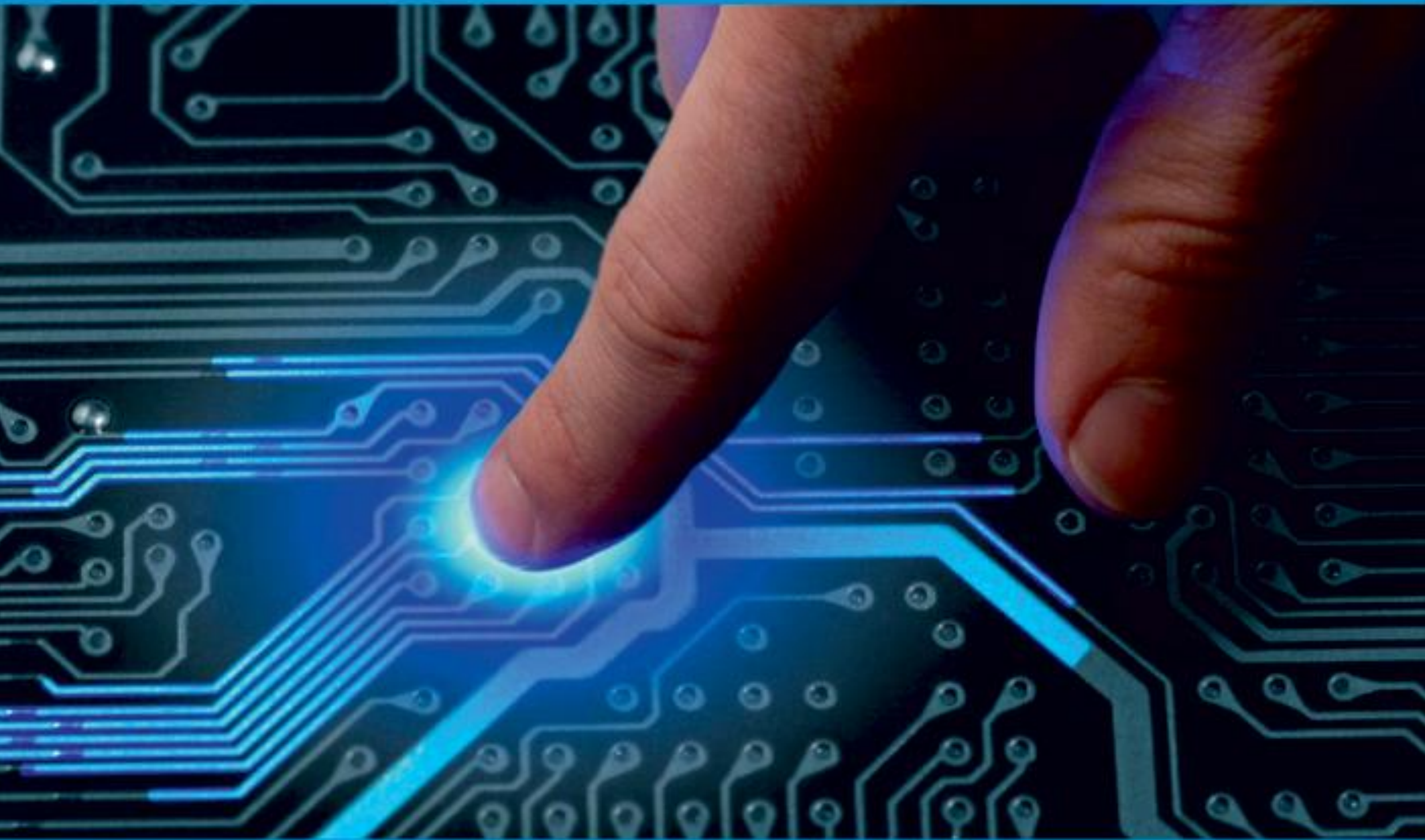

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Implementation of A Wild AnimalIntrusion Detection Model

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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. The system, driven by edge computing, ensures real-time responsiveness to mitigate crop raiding. The workflow commences with the activation of the camera by the edge computing device, triggering the deployment of an advanced Animal Intrusion Detection Model. 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. By incorporating cutting-edge technologies, the Integrated Wildlife Management System offers a robust and adaptable solution for safeguarding crops from a variety of wild animals, such as elephants, wild boar, and deer. By leveraging cutting-edge technology, the proposed solution seeks to strike a balance between protecting crops and minimizing environmental impact. 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.

KEYWORDS: Temporal Convolutional Networks.

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 yearsago, 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 developmentof 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. This trend holds for farming not only in developed countries but also in developing countries, where deployments in ICT (e.g., use of mobile phones, access to the Internet) are being adopted at a rapid pace and could become the game-changers in the future (e.g., in the form of seasonal drought forecasts, climate-smart agriculture).

AI with IoT in Smart Farm: Agriculture 5.0 Era, Artificial Intelligence, IoT & Machine Learning provides an interdisciplinary, integrative overview of the latest developments in the domain of smart farming. AI in agriculture, also known as precision agriculture, is the application of artificial intelligence (AI) solutions in the agricultural industry. At the core of the advanced AI, IoT, big data and analytics-based solutions for smart farming is the collection and analysis of data for generating real-time relevant insights at scale and speed, leading tophenomenally higher yield and better utilization of resources. The evolution of technologies such as AI, Machine Learning (ML), Deep Learning, and big data analytics, is encouraging the use of smart machines and intelligent robots in agriculture. Called precision or smart agriculture, these technologies are paving the way for improving agriculture. AI combined with big data, cloud, IoT, and ML is transforming rural farmlands with a range of data- driven solutions- from automatic detection of drought patterns to tracing the ripening patterns of apples or tomatoes, to smart tractors that weed out the diseased and sick plants. IoT devices are sensor-equipped tools that areconnected to the internet. Combined with artificial intelligence, such smart devices can be implemented to increase yields and productivity, while reducing crop failures. They do so by monitoring, analyzing, and forecasting data. These IoT devices can be used in tractors and trucks, as well as in fields, soil, and plants, to collect data in real time. Farmers gain insight into light, temperature, and moisture levels. They can analyze topography and soil, or leverage satellite and radar imaging technologies through smart algorithms. The data collected is combined with other available information, such as historical weather and crop data, or aerial imagery. With all of the data gathered, machine learning models are trained to identify patterns – making AI yield prediction a reality.

III. OBJECTIVE

The main aim of the current work is to develop a device to protect crops from damage by wild animals by diverting them from the farms, without harming them physically. The objective of the project is to design, deploy, and assessment of an intelligent smart agriculture repelling and monitoring IoT system based on embedded edge AI, to detect and recognize the animals, as well as generate ultrasonic signals tailored to each species of the animals. Untamed life checking and investigation have been in dynamic research fields for the last numerous decades. This work mainly concentrates on creature identification from common scenes gained by the camera and intimates the farmland owner and also stores the images in the camera trap database. This camera trap database is utilized totrack the animals which enter the farmland and damage the crops.

IV. FLOW CHART

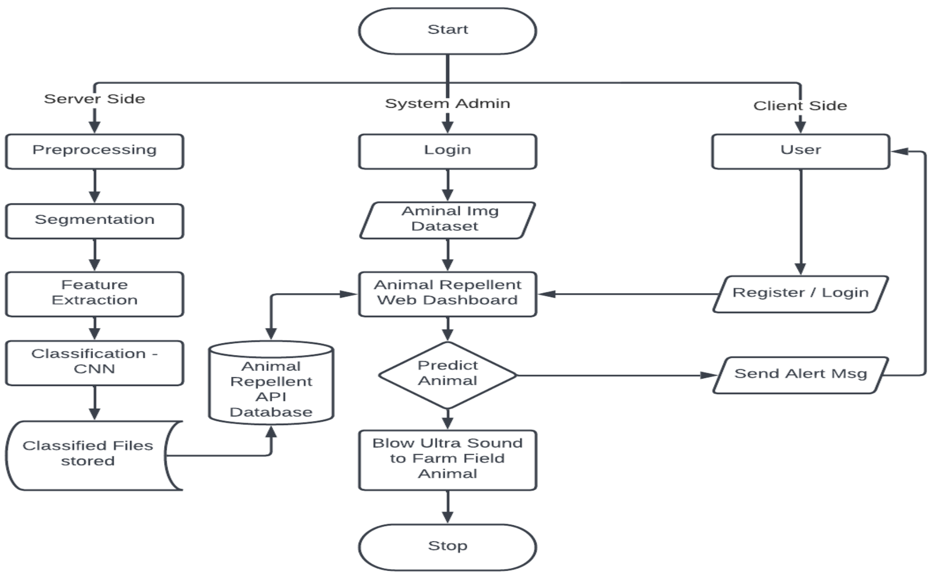

Figure4.1: Flow Chart

V. EXISTING SYSTEM

Wild animals are a special challenge for farmers throughout the world. Animals such as deer, wild boars, rabbits, moles, elephants, monkeys, and many others may cause serious damage to crops. They can damage the plants by feeding on plant parts or simply by running over the field and trampling over the crops. Therefore, wild animals may easily cause significant yield losses and provoke additional financial problems. Another aspect to consider is that wild animal crop protection requires a particularly cautious approach. In other words, while utilizing his crop production, every farmer should be aware and take into consideration the fact that animals are living beings and need to be protected from any potential suffering.

Farmer's Traditional Approach: There are different existing approaches to address this problem which can be lethal (e.g., shooting, trapping) and non-lethal (e.g., scarecrow, chemical repellents, organic substances, mesh, or electric fences), firecrackers, bright lights, fire, beating drums, and dogs. Non- chemical control of pocket gophers. 22 rimfire rifles or a shotgun can be used to dispatch woodchucks. Some motion-activated water sprayers have been developed that spray birds when they break the motion- detecting

Wire fences: constructed of metal wires woven together forming a physical barrier. The fencesare effective, long-lasting, and require relatively little maintenance. However, they are expensive and recommended only for the protection of high-value crops.

Plastic fences: polypropylene fences are generally less expensive and easier to install and repair than other types. Additionally, these fences are widely acceptable and meet various regulations. Their disadvantage includes their short lifespan (up to 10 years) and questionable effectiveness in areas with a higherpossibility of wild animal crop damage.

VI. 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.

AI Computer Vision Module.
The TCN and WildNet form the core of the computer vision module, offering real-time video analysis for accurate detection and recognition of animal species. This component processes high-resolution imagery captured by cameras deployed in agricultural areas, enhancing the system's ability to identify and classify wildlife accurately.

Convolutional Layer: Convolutional layer performs the core building block of a Convolutional Network that does most of the computational heavy lifting. The primary purpose of Convolution layer is to extract features from the input data which is an image. Convolution preserves the spatial relationship between pixels by learning image features using small squares of input image.The input image is convoluted by employing a set of learnable neurons. This produces a feature map or activation map in the output image and after that the feature maps are fed as input data to the next convolutional layer.

Pooling Layer: Pooling layer reduces the dimensionality of each activation map but continues to have the most important information. The input images are divided into a set of non-overlapping rectangles. Each region is down-sampled by a non-linear operation such as average or maximum. This layer achieves better generalization, faster convergence, robust to translation and distortion and is usually placed between convolutional layers.

ReLU Layer: ReLU is a non-linear operation and includes units employing the rectifier. It is an element wise operation that means it is applied per pixel and reconstitutes all negative values in the feature map by zero. In order to understand how the ReLU operates, we assume that there is a neuron input given as x and from that the rectifier is defined as $f(x)= \max(0, x)$ in the literature for neural networks.

VII. SYSTEM MODULES

Modules Description

Wildlife Defense Web App
This Wildlife Defence Web App is designed and developed using Python with Flask as the web framework, MySQL for database management, and Bootstrap for a responsive and visually appealing user interface. The web app incorporates a secure user authentication system, allowing administrators and farmers to access different functionalities based on their roles. The system allows administrators to train and build WildNet models through a user-friendly interface. Image classification and labelling functionalities facilitate the training process, and the deployment of trained models to edge devices ensures efficient real-time detection. Administrators can configure ultrasound repellents for each species through an intuitive panel. This feature enhances the system's defence mechanism by customizing and deploying ultrasound emissions based on WildNet model predictions. A map interface provides a geographical overview of edge device locations and active repellent zones. This feature enables administrators and farmers to remotely monitor wildlife activities across fields. Remote access is facilitated, allowing farmers to view real-time field data from any location via the internet.

Use Interface
Login: 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.
Upload Datasets: 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.
Build and Train WildNet Model: 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.

WildNet Model: Build and Train
This module combines dataset collection, pre-processing, advanced image processing techniques, and CNN-based classification to build and train the WildNet model. The integration of the trained model into the Wildlife Defence Web AppFirmware enhances the system's capability to detect and categorize wildlife, providing a robust defence mechanism for agricultural fields.

Animal Identification
After capturing the animal image from the Farm Camera, the image is given to animal detection module. This module detects the image regions which are likely to be human. After the animal detection using Region Proposal Network (RPN), animal image is given as input to the feature extraction module to find the key features that will be used for classification. The module composes a very short feature vector that is well enough to represent the animal.

Animal Intrusion Predictor
The Animal Intrusion Predictor module with Temporal Convolutional Networks (TCN) is designed to identify and predict the presence of animals in input images, live video streams, or recorded videos. TCN is a type of neural network architecture commonly used for sequence modeling, making it well-suited for tasks involving temporal dependencies, such as video analysis.
Input Modalities
Image Input: Users can provide single images as input to the system for animal detection.

Live Video Input: The module can process live video streams in real-time, identifying animals as theyappear.

Video Input: Users can analyze pre-recorded videos, allowing retrospective analysis of animal intrusion.

Software testing is an essential step in the development of a system that combines computer vision using TCN for detecting and recognizing animal species, and specific ultrasound emission for repelling them. The following types of testing can be performed:

Types of Testing
Unit Testing: Unit testing involves testing individual software components, such as functions or methods, to ensure that they perform as expected. In the case of this system, unit tests can be performed on the TCN model, ultrasound emission generator, and other software components.

Integration Testing: Integration testing involves testing the interaction between different software components to ensure that they work together as expected. In the case of this system, integration tests can be performed on the computer vision and ultrasound emission components to ensure that they work together seamlessly

Functional Testing: Functional testing involves testing the system's functionality against the requirements specification. In the case of this system, functional tests can be performed to ensure that the system can detect and recognize animal species and emit the appropriate ultrasound frequency for repelling them.

Performance Testing: Performance testing involves testing the system's performance under different conditions, such as high load or limited resources. In the case of this system, performance tests can be performed to evaluate the system's detection and recognition speed, as well as the effectiveness of the ultrasound emission for repelling the detected animal species.

Acceptance Testing: User acceptance testing involves testing the system's usability and user interface against user expectations. In the case of this system, user acceptance tests can be performed to evaluate the ease of use and clarity of feedback provided by the user interface.

Security Testing: Security testing involves testing the system's security features, such as data encryption and access controls, to ensure that they are properly implemented. In the case of this system, security tests can be performed to ensure that the system is protected against unauthorized access and data breaches.

VIII. FUTURE ENHANCEMENT

Future enhancements can improve the functionality, user experience, and effectiveness of the animal- repellent system.
Integration with smart home systems: The Animal Repellent system can be integrated with existing smart home systems such as Google Home or Amazon Alexa to allow for voice commands and automated responses. This can enhance the user experience and provide more convenience.

Mobile app integration: The Animal Repellent system can have a mobile app that allows users to remotely monitor and control the system from their smartphones. The app can also provide notifications and alerts to users when the system detects animal species.

Integration with security systems: The Animal Repellent system can be integrated with existing security systems such as CCTV cameras or motion sensors to provide a more comprehensive security solution. This can enhance the system's overall effectiveness and provide more peace of mind to users.

IX. CONCLUSION

Agricultural farm security is a widely needed technology nowadays. To accomplish this, a vision-based system is proposed and implemented using Python and OpenCV, and developed an Animal 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 recognition of the presence and species of animals in real-time and also to avoid crop damage caused by the animals. Based on the category of the animal detected, the edge computing device executes its TCN Animal Recognition model to identify the target, and if an animal is detected, 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. The proposed TCN was evaluated on the created

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animal database. The overall performances were obtained using different numbers of training images and test images. The obtained experimental results of the performed experiments show that the proposed TCN gives the best recognition rate for a greater number of input training images (accuracy of about 98 %). This project presented a real-time monitoring solution based on AI technology to address the problems of crop damage against animals. This technology used can help farmers and agronomists in their decision-making and management process.

REFERENCES

1. M. De Clercq, A. Vats, and A. Biel, ``Agriculture 4.0: The future of farming technology," in Proc. World Government Summit, Dubai, UAE, 2018, pp. 11-13.
2. Y. Liu, X. Ma, L. Shu, G. P. Hancke, and A. M. Abu-Mahfouz, ``From industry 4.0 to agriculture 4.0: Current status enabling technologies, and research challenges," IEEE Trans. Ind. Informat., vol. 17, no. 6, pp. 432 4334, Jun. 2021.
3. M. S. Farooq, S. Riaz, A. Abid, K. Abid, and M. A. Naeem, ``A survey on the role of IoT in agriculture for the implementation of smart farming," IEEE Access, vol. 7, pp. 156237-156271, 2019.
4. K. Kirkpatrick, ``Technologizing agriculture," Commun. ACM, vol. 62, no. 2, pp. 14-16, Jan. 2019.
5. A. Farooq, J. Hu, and X. Jia, ``Analysis of spectral bands and spatial resolutions for weed classification via deep convolutional neural network," IEEE Geosci. Remote Sens. Lett., vol. 16, no. 2, pp. 183-187, Feb. 2018.
6. M. Apollonio, S. Ciuti, L. Pedrotti, and P. Banti, ``Ungulates and their management in Italy," in European Ungulates and Their Management in the 21th Century. Cambridge, U.K.: Cambridge Univ. Press, 2010, pp. 475-505.
7. A. Amici, F. Serrani, C. M. Rossi, and R. Primi, ``Increase in crop damage caused by wild boar (Sus scrofa L.): The `refuge effect,'" Agronomy Sustain. Develop., vol. 32, no. 3, pp. 683-692, Jul. 2012.
8. S. Giordano, I. Seitanidis, M. Ojo, D. Adami, and F. Vignoli, ``IoT solutions for crop protection against wild animal attacks," in Proc. IEEE Int. Conf. Environ. Eng. (EE), Mar. 2018, pp. 1-5.
9. M. O. Ojo, D. Adami, and S. Giordano, ``Network performance evaluation of a LoRa-based IoT system for crop protection against ungulates," in Proc. IEEE 25th Int.Workshop Comput. Aided Modeling Design Commun. Links Netw. (CAMAD), Sep. 2020, pp. 1-6.
10. H. E. Heefner and R. S. Heffner, ``Auditory perception," in Farm Animals and the Environment, C. Phillips and D. Piggins, Eds. Wallingford, U.K.: CAB International, 1992.
11. https://www.indiatimes.com/news/india/in-the-battle-between-man-vs-wild-highways-railway- lines-emerge- as-new-challenges-375504.html
12. https://adventuresinmachinelearning.com/neural-networks-tutorial/
13. https://github.com/tensorflow/models

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