AI-based Animal Intrusion Detection System for Human-Wildlife Conflicts in Bhutan

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Abstract
This paper presents the proposed prototype of an Animal Intrusion Detection System powered by Artificial Intelligence of Things (AIoT) technology to address growing challenges of human-wildlife conflicts (HWC) in Bhutan. The major incursions of wildlife in the agriculture fields possess a major threat to sustainable food security and farmer livelihoods in the country. While the government has implemented various mitigation measures like electric and chain-link fencing, and animal repellent system, these solutions have notable limitations. Therefore, our AI-based system aims to provide as an alternative smart agriTech solution to address HWC. The system utilizes a Raspberry Pi 4, a night vision-based camera, an ultrasonic sensor and YOLOv8 deep learning algorithm for real-time animal detection and classification. The YOLO model was trained on a dataset of 30,800 images featuring seven local wildlife species which are common in raiding the crop in Bhutan. The system, upon detecting an intrusion on farmland, will automatically transmits an alert notification to farmers via a mobile app over a cellular network, enabling timely intervention to mitigate the crop damage. When the internet connection is down, the system will notify the farmers through SMS and Dial. In a controlled laboratory environment, the prototype achieved a detection accuracy of 95.7%. These finding indicates a promising alternative innovative agriTech solution for mitigating crop losses, enhancing food security and enhancing farmer livelihoods. However, the prototype requires field validation and further AI model training with a more extensive real animal dataset collected through its pilot implementation to evaluate the system's performance and robustness under real-world conditions of the agriculture field.
Key Words: *Human-wildlife Conflict (HWC), Artificial Intelligence of Things (AIoT), Object Detection, Deep Learning, YOLO, Animal dataset, Camera, Real-time notification, Food Security.*

1. INTRODUCTION

Food security is one of the United Nation's development agenda for the 21st century, reflected in its central role within the Sustainable Development Goals (SDGs). As part of this global framework, agriculture is particularly significant for countries like Bhutan, where it remains a cornerstone of the national economy and rural livelihoods.

In Bhutan, the agriculture sector serves as a primary contributor to the national economy, employing approximately 55.78% of the population. However, the country faces multiple challenges in achieving self-sufficiency in food production and ensuring sustainable food security. Among the major obstacles including climate change, natural disasters and water scarcity, the HWC is regarded as the most significant threat to agricultural productivity. According to survey data collected from 105 households in Paro, all respondents reported experiencing conflicts related to animal intrusions in their fields. Notably, 98.1% of these conflicts were associated with crop raiding, while the remaining 1.9% involved cattle predation (Thinley, 2019). Further, (Sangay et.al., 2023) provides detailed insights into the extent of crop damage caused by wild animals in Bhutan and reporting significant losses. This study also emphasizes the impact by HWC on food self-sufficiency and the socio-economic consequences, including labor shortages and migration.

The HWC has been considered as a global issue particularly for agriculture-dependent nations. The expansion of human settlements and the increasing demand for natural resources have contributed to habitat loss, thereby exacerbating such conflicts in many regions. In Bhutan, these conflicts have intensified over the years, with growing socio-economic development activities. The depletion of natural habitats has compelled wild animals to encroach upon human settlements, particularly agricultural fields, in search of food and shelter. This encroachment leads to the destruction of crops, damage to personal property, livestock predation, and, in some unfortunate instances, injuries and fatalities among both humans and animals. Addressing the root causes of HWC is inherently complex and cannot be resolved through simple or immediate solutions. Furthermore, these conflicts pose a significant threat to the conservation and survival of various wildlife species (Africa, 2014).

To mitigate HWC, various measures have been implemented to safeguard crops from wildlife intrusion. Traditionally, farmers in Bhutan have relied on manual surveillance, often staying overnight in temporary huts to guard their fields, a common approach that remains prevalent in rural areas. Additionally, some farmers construct physical barriers, such as fences, to deter animals from entering their fields. Recognizing the need for more effective solutions, the Royal Government of Bhutan has introduced several mitigation strategies, including electric fencing and animal-repellent systems, and is now considering the deployment of chain-linked fencing to protect farmlands. However, these measures have inherent limitations, necessitating further exploration of innovative and sustainable solutions to effectively address this pressing issue.

2. RELATED WORK

The increasing prevalence of human-wildlife conflict presents a significant challenge for farmers in Bhutan and other agriculture-dependent nations. Wild animals frequently cause substantial damage to crops, livestock, and property, and in some cases, pose direct threats to human life. Traditional methods of mitigating such conflicts, including electric fencing and the use of guard dogs, are often costly, ineffective, and potentially harmful to wildlife. Similarly, conventional approaches such as trenches, manual surveillance, and habitat protection strategies have proven to be temporary, economically unsustainable, and insufficiently reliable. Moreover, these measures may inadvertently pose risks to both humans and wildlife, highlighting the need for more sustainable and ethically sound solutions.

Both governmental and non-governmental organizations have undertaken initiatives to assist farmers in protecting their crops from wildlife intrusion by implementing various mitigation strategies. Among these, farmers have been provided with and encouraged to install electric fencing systems in their fields. However, electric fencing has proven to be an inadequate long-term solution, presenting significant maintenance challenges. Poor maintenance efforts have frequently resulted in the system failing to deliver the expected outcomes and, in some cases, have even posed safety risks to farmers (Dorjee et al., 2021).

The animal repellent system was developed by the Agriculture Machinery & Technology Center (AMTC, Paro), Department of Agriculture, Ministry of Agriculture & Livestock using the PIR sensor to detect the animal, trigger the smart scarecrow with a sound & lighting system to repel the animal from fields and also sends an alert message. This system was piloted in 6 sites in Bhutan and found useful in addressing HWC. However, this system lacks AI-based detection method and generates false alert messages that regularly disturbs the farmers and producing false amplified sound disturbing the near-by local community. Hence, there is a pressing need to create an alternative solution with better efficiency to addressing HWC. Recent advancements in deep learning have witnessed the development of image classifiers that have already surpassed human accuracy, leading to high demand for AI to work effectively within the IoT domain.

A smart animal detection system for crop protection has been developed using the YOLOv5 model and Raspberry Pi, enabling real-time animal detection and alerting farmers via a mobile application (Norzang et al., 2023). However, this system employs a standard webcam for image capture and relies on a YOLO model trained on a limited dataset of 9,900 images representing only five animal species commonly responsible for crop damage in Bhutan. As a result, the system remains in its initial prototype stage, demonstrating promising but preliminary outcomes.

Similarly, a machine learning-based Acoustic Repellent System has been proposed in India to mitigate crop damage caused by wild animals (Ranparia et al., 2020). This system utilizes a convolutional neural network (CNN)-based machine learning model, Raspberry Pi, and an infrared (IR) camera. However, it employs a frequency generator for animal recognition and is limited to detecting only three species: deer, boar, and Nilgai.

Another approach, the Intrusion Detection and Repellent System for wild animals, has been introduced in India to address HWC. This system leverages the YOLOv3 model, trained on five animal classes, alongside Raspberry Pi Zero-W and dual passive infrared (PIR) sensors for object detection. Additionally, it incorporates a light buzzer as a repellent mechanism (Patil et al., 2022). While these systems represent important advancements in technology-driven wildlife mitigation, their effectiveness remains constrained by limited training datasets, species detection capabilities, and the scalability of their deployment.

2.1. YOLO v8 Model

YOLOv8, the eighth generation of the You Only Look Once (YOLO) deep learning algorithm, represents a state-of-the-art advancement in object detection, offering enhanced performance over its predecessors (Johnson, 2023). Its improvements in accuracy, speed, and efficiency make it highly applicable across various computer vision domains. YOLOv8 addresses the limitations of earlier versions through a modular and scalable architecture composed of three key components: the backbone, the neck, and the head.

The backbone is responsible for detecting and extracting features from input images, while the neck facilitates feature fusion by connecting the backbone to the head. The head then processes this information to predict bounding boxes, object classifications, and confidence scores for each detected object. Additionally, YOLOv8 supports multiple variants, such as YOLOv8-Nano and YOLOv8-Large, allowing users to select the most suitable model based on specific implementation requirements.

3. METHODOLOGY

This section outlines the methodology employed in the development and testing of the proposed AIoT-based Animal Intrusion Detection System, as illustrated in Fig.1. A comprehensive literature review was conducted to examine existing methods, technologies, and systems relevant to the project. Through this review, gaps and limitations in current approaches were identified, enabling the formulation of potential improvements. Additionally, studies that successfully implemented similar systems were analyzed and utilized as baseline references for the development of a system tailored for use in Bhutan.

Following the procurement of hardware components, the development of the mobile application, IoT System, and AI model training were carried out simultaneously, with systematic documentation of each phase. The AI model was initially trained on a limited dataset using Google Collab. Subsequently, during a vacation internship program, model training was extended to high-performance computing (HPC) provided by the GovTech agency to facilitate training on a large dataset. Upon completion of model training, the AI model was integrated with the IoT system, followed by performance evaluation and functionality testing, particularly focusing on model accuracy and real-time notification capabilities.

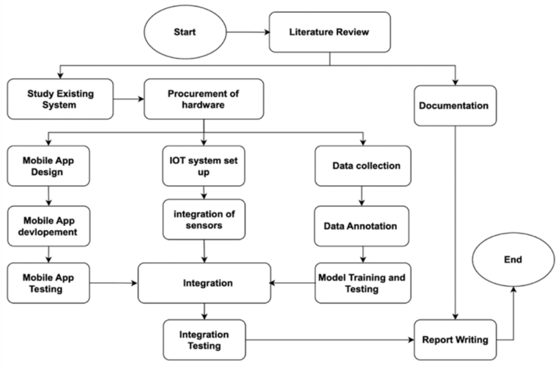

Fig. 1: *Methodology*

3.1. Mobile App & Web App

An extensive study was carried out on various frameworks to select the most appropriate one for mobile app development for the system. A simple prototype of the app was designed to get a clear view of the features to be added to the application. A database in the cloud was designed to store some detailed information about detected animals in the field and also facilitate communication between the IoT system and mobile app. The app will be used by the farmers to receive a notification alert message in real-time when intruded wild animals are detected in the field. The web app will used by system administrator to manage the users and access the databases for decision making supports.

3.2. IoT System

The IoT system was developed using the Raspberry Pi 4 (RPI) Model B, night vision-based Arducam, and ultrasonic sensors. The RPI was configured as a microcontroller and integrated with the Arducam and ultrasonic sensors to facilitate system functionality. The trained AI model was then embedded within the RPI microcontroller to enable automated animal detection and classification. The system is designed for deployment in agricultural fields with high incidences of wildlife intrusion and perform its operation by detecting motion in real-time. Upon detecting movement, the system activates the camera, which captures video footage and transmits it to the RPI microcontroller. The embedded AI model subsequently processes the footage to identify and classify the detected animals, triggering an alert notification to inform farmers of potential threats over the cellular communication network using GSM module.

3.3. Data Pre-processing & Model Training

Images representing seven classes of animals were sourced from publicly available datasets, including Kaggle, Roboflow, and Google Images. To enhance dataset diversity and improve model generalization, various data augmentation techniques were applied using OpenCV and Python. Additionally, a dataset comprising 9,900 images, prepared by (Norzang et al., 2023), was incorporated, resulting in a total dataset of approximately 30,800 images. These images were manually annotated using the web-based MakeSense AI tool to ensure precise labeling for model training. The dataset was utilized to train both large and nano variants of the YOLOv8 model, enabling a comparative analysis based on key performance metrics such as accuracy, loss reduction, and power efficiency. Following model training, the optimized model was integrated into the IoT system and deployed within a mobile application. The complete system was then tested in a controlled experimental lab setup to evaluate its effectiveness in detecting animal intrusions.

4. SYSTEM OVERVIEW

As illustrated in Figure 2, the conceptual framework of the proposed system outlines its operational workflow, from detecting animal intrusions in agricultural fields to delivering real-time notifications to farmers. The system comprises three primary components: IoT system in the agricultural field, the server systems on cloud, and the client device with mobile app which are connected over cellular communication networks.

We have a plan to integrate the proposed AI-based system with existing animal repellent system developed by AMTC for automatic intervention of repelling the intruded animal.

In the agricultural field, the IoT system comprising a ArduCamera, AI model, and various sensors is strategically positioned based on field-specific requirements. Critical factors such as camera height and angle are considered to capture and ensure optimal detection of intruding animals. The IoT system continuously monitors the environment, with the ultrasonic sensor detecting nearby objects and triggering the camera.

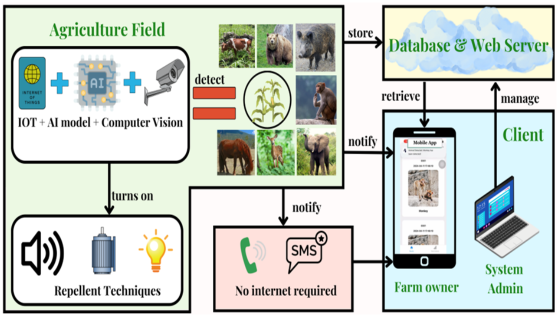

Fig 2: *Conceptual framework of the system*

Once the AI model identifies an animal, the detected information is published to the Hive MQTT broker, to which both the mobile application and database server are subscribed. The published data is then relayed as a real-time notification alert to the client (farm owner) via a mobile app while simultaneously being stored in a MongoDB database for future data analysis. These data transmission will take place over cellular communication networks using GSM technology. However, when the internet is down, IoT system gets disconnected with MQT will notify the farmers through SMS & Dial where detected animal details cannot be stored in the database. The overall control flow of the system is depicted in Figure 3.

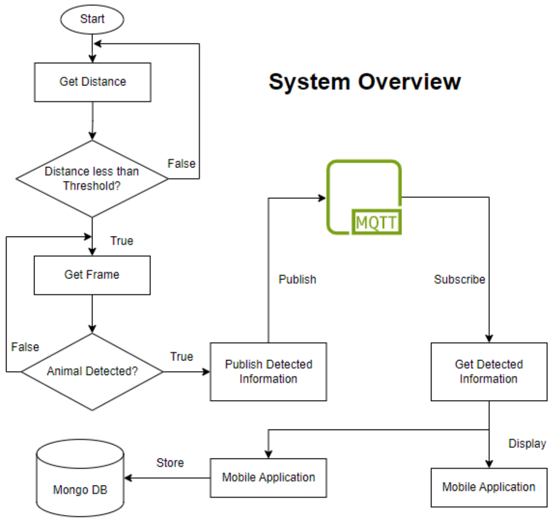

Fig 3: *Overall Control Flow of System*

The AI model is based on YOLOv8, an advanced object detection algorithm, trained on a dataset of 31,800 images encompassing seven animal classes: Bear, Boar, Cattle, Deer, Elephant, Horse, and Monkey. When embedded within the Raspberry Pi, the YOLOv8 model analyzes incoming image frames to detect and classify animals within the trained categories. If an animal is identified, the model returns the detected species, bounding box coordinates, and confidence score.

To facilitate user interaction, a mobile application was developed using the React Native framework, which supports cross-platform functionality. The application features a responsive design and an intuitive user interface, ensuring ease of use for farmers in monitoring and responding to animal intrusions efficiently.

5. RESULTS AND DISCUSSION

5.1. Comparative Analysis of the Trained Models

A total of 12 models were trained using different datasets and hyperparameter configurations to optimize performance. The initial two models were YOLOv5, trained on a dataset of 9,900 images representing six animal classes. Subsequently, three YOLOv8 large models were trained: two using the same 9,900-image dataset with varying batch sizes and one with an expanded dataset of 12,000 images. Figure 4 presents the mean average precision (mAP) scores for these five models.

A comparative analysis of the models trained on identical datasets revealed that YOLOv8 outperformed YOLOv5 in terms of accuracy and detection capabilities. Building upon these findings, six YOLOv8 nano models were further trained using a dataset that included seven animal classes. Among them, seven models were trained on an extended dataset of 30,800 images, each employing different hyperparameter configurations. The table below provides an overview of the six models and their respective mean average precision scores.

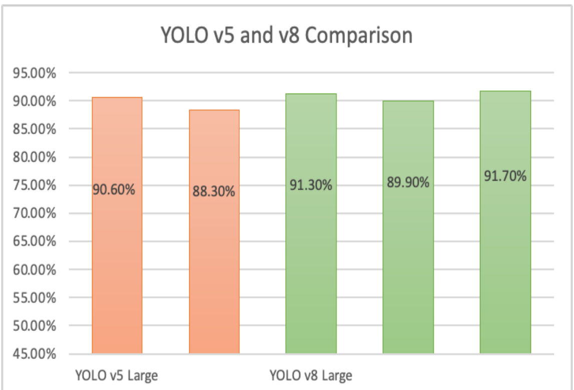

Fig 4: *YOLOv5 and YOLOv8 Comparison*

Table 1: *Details of trained YOLOv8 nano models*

SI No.	Model Type	Image Size	Instances	Batch Size	Epoch Size	mAP	Recall	Precision	Inference speed
1	Yolo v8 nano	640x640	Not balanced	64	150	90.663	90.721	82.529	≈1000ms
2	Yolo v8 nano	640x640	balanced	32	150	94.106	88.10	90.08	≈1000ms
3	Yolo v8 nano	640x640	balanced	64	150	94.128	89.567	88.202	≈1000ms
4	Yolo v8 nano	320x320	Not balanced	32	150	95.104	89.917	92.921	≈550ms
5	Yolo v8 nano	320x320	Not balanced	64	150	94.959	88.729	94.191	≈550ms
6	Yolo v8 nano	320x320	Not balanced	64	300	95.771	90.351	94.294	≈550ms

Model 6 demonstrated higher precision and significantly reduced image processing time compared to the initial models. This improvement was achieved by optimizing the image size to 320×320, which enhanced processing efficiency. The model's performance was further optimized by utilizing a batch size of 64 and increasing the number of epochs, which proved to be an ideal configuration given the dataset size used in this study.

5.2. System Integration Results

Following the integration of the selected AI Model 6 with the IoT system and its associated components, the system prototype was tested under controlled conditions in an experimental laboratory setup on the college campus. The testing process involved the use of printed images of animals as well as recorded videos containing animal movements. During the evaluation, a delay was observed in the system's response time, with the mobile application taking approximately 5 to 30 seconds to display notifications triggered by the IoT system upon detecting an animal intrusion. This latency was primarily attributed to the AI model requiring 500 to 600 milliseconds to process each image frame and accurately detect the presence of animals.

6. CONCLUSION

This study has demonstrated the feasibility of utilizing an AIoT-based Animal Intrusion Detection System to mitigate human-wildlife conflict in Bhutan's agricultural sector. By integrating the YOLOv8 model with an IoT system, we have developed a real-time solution capable of detecting and classifying wildlife intrusions, subsequently providing farm owners with real-time notification alerts via a mobile app over cellular communication network. The YOLOv8 model was successfully trained on a dataset of 30,800 animal images and, upon integration with the Raspberry Pi, achieved an accuracy of 95.7%. The system prototype yielded promising results when tested in a controlled experimental laboratory environment. These findings suggest that the proposed AgriTech solution holds significant potential in reducing crop damage, enhancing food security, and improving the livelihoods of rural communities in Bhutan.

Despite its promising outcomes, the current system operates optimally under controlled conditions, primarily due to the AI model being trained on a limited dataset of animal images sourced from online platforms and its ability to detect only seven specific animal species.

Therefore, further improvements are necessary to enhance the system's performance and robustness in diverse agriculture landscapes. Future research should focus on expanding the dataset to include a broader range of wildlife, refining the AI model, improving the mobile and web applications, and conducting extensive field testing. These enhancements will be crucial in optimizing the system's performance under diverse environmental conditions and effectively addressing human-wildlife conflict in Bhutan's agricultural sector.

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