



Convolutional Neural Network-based Model for Intrusion Detection in Poultry Farms

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Received: January 23, 2025 / Accepted: March 25, 2025
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Abstract

This research develops a convolutional neural network-based model for intrusion detection in poultry farms. Poultry farm is a vital sector agriculture that aims at meeting the growing demand for high-protein food. However, managing large poultry populations poses challenges, particularly in monitoring birds' health and detecting intrusions. This study leverages CNN to automate farm surveillance, enabling continuous monitoring, early anomaly detection, and rapid response to threats such as animal invasions. The proposed intrusion detection system significantly enhances poultry welfare, strengthens farm security, and advances machine learning applications in agriculture. Experimental results demonstrate the model's effectiveness, achieving a high Mean Average Precision (mAP) of 0.995. The confusion matrix indicates accurate classification, correctly identifying 25 out of 27 chickens, all 16 owners, and 11 out of 12 other subjects, while background images were properly detected.

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Keywords: Convolutional Neural Network (CNN), Intrusion Detection, Machine Learning, Smart Poultry Farm, Deep Learning, Image Classification.

1.0 Introduction

Smart farming is superior method of managing a farm and is becoming prevalent in contemporary agricultural practices (Amir *et al.*, 2023; Kethineni *et al.*, 2024). Animal intrusion in the farming area causes significant losses and threatens not only the safety of farmers but also contributes to crop damage, making the provision of effective solutions for human-animals conflict a highly significant challenge all over the world (Mamat *et al.*, 2022). An essential part of agriculture that helps meet the growing demand for high-protein food is poultry rearing. However, there are several obstacles to overcome in the efficient management of poultry farms, particularly when working with huge bird populations. Intruders, ranging from unauthorized persons to predators, pose a serious threat to poultry and cause losses to poultry farmers. To provide the best farm management and animal welfare, accurate monitoring and detection of possible intrusion require innovative technology (Mahesh, 2022). In talking of innovative technology, a subset of artificial intelligence known as machine learning (ML), which uses large datasets to find complex and unexpected patterns or information and then uses this knowledge to make informed decisions, comes into play (Ekong *et al.*, 2022).

Computer systems can be made to be intelligent without explicit programming and reprogramming by learning from their experiences and this is what Artificial Intelligence (AI) is about. By utilizing the capabilities of ML, particularly Convolutional Neural Networks (CNN), this research seeks to proffer solutions to the aforementioned problems. CNNs are a kind of deep learning algorithm that draws inspiration from the human visual system. They are a great fit for evaluating visual data from cameras because they have demonstrated a high level of effectiveness in image identification tasks.

Because CNNs can accurately learn both spatial and hierarchical characteristics from huge images, they are the most suitable for image identification tasks like this one. The research seeks to address these challenges by developing an advanced intrusion detection system for poultry farms using Convolutional Neural Networks (CNNs). The goal is to automate monitoring, identify potential threats, such as human intruders or non-poultry animals, in real-time, and trigger alarms and notify farm owners immediately upon detecting suspicious activity. This research aims to design a machine-learning algorithm capable of accurately and efficiently detecting intruders in poultry farms.

The research work offers significant benefits for poultry farms. Continuous monitoring ensures prompt identification and response to any threats, improving overall poultry well-being. Early detection of intruders minimizes economic losses due to theft and predatory actions. The system strengthens security measures, protecting valuable poultry assets and farm infrastructure. It contributes to the advancement of machine learning applications in animal husbandry and agriculture.

This research holds the potential to revolutionize poultry farm management by providing a robust and reliable solution for intrusion detection, ultimately contributing to improved animal welfare, enhanced security, and increased profitability for poultry producers.

Many studies have been conducted about intrusion detection. One of the studies was a camera trap detector system to automatically detect, classify, and count animals in camera trap images. Tabak *et al.* (2020) developed these models to possess the capability to autonomously detect, count, and categorize prevalent North American domestic and wild species within camera trap images. The

"CameraTrapDetectoR" package generates predictions in the form of a data frame and a flat file. The model performed well on both validation datasets and out-of-distribution testing datasets as the mean average precision values ranged from 0.80 to 0.96.

Several research has been carried out on the area of intrusion detection. One of such was by Bhumika *et. al.* (2022), who with the help of convolutional neural networks (CNN), created a system that allowed them to identify animals as they entered the farmland. The main goal of the project was to maintain continuous surveillance throughout the entire farm by using cameras that recorded the surroundings around the clock. By combining the CNN algorithm with Xgboost, they were able to identify instances of animal intrusion and promptly notify farmers when such events occur and to trigger disruptive sounds to scare it away. The project addressed one of the major hazards in recent years, which is crop damage brought on by wild animal intrusions.

Using machine learning and deep learning models, Thangarasu *et. al.* (2019) created an algorithm to aid in the identification of animal species on camera-trapped images. The main goal of the research was to investigate various ML algorithms, such as Random Forest (RF) and Support Vector Machine (SVM), along with deep learning models, such as Inception V3 and AlexNet, to classify animal species. From the experiments, it was found that InceptionV3 outperforms SVM, Random Forest, and AlexNet in terms of accuracy. This emphasizes that using InceptionV3, precise techniques, and enough data could lead to highly accurate classification. The project yielded accuracy results for random forests, support vector machines, and deep learning models like Alexnet and InceptionV3 of 91.8%, 84.7%, 94.7%, and 98.0%. He concluded that the machine learning algorithms

were constantly surpassed by the deep learning models in this regard.

Jeevitha and Arul (2020) proposed an animal intrusion alert system that used wireless sensors to automatically send alerts, along with accompanying images, to forest authorities and landowners. Early warning alerts were made possible by that system, which made it easier to take the proper action given the type of intruder. By combining sensors to track the movements of the animals with cameras to take pictures, the photos were processed using image processing methods so that they could be classified. After that, a GSM module is utilized to send SMS alert notifications to the landowner or the forest department. The survey helped in understanding different approaches, instruments, and experimental configurations to protect human life from animal encroachment.

Sabeenian *et. al.* (2020) leveraged machine learning techniques for the identification of wild animals entering farmlands. This was accomplished using the deep neural network approach. The project involved consistent monitoring of the entire farm through a camera that recorded the surroundings throughout the day. Through the utilization of a machine learning model, they could identify the presence of animals and employ appropriate sounds to deter them harmlessly. The proposed model was trained on the image dataset of monkeys, boars, and elephants. If any of the animals that were trained were detected during the live capture, a repelling sound was played to drive away the animal with the help of speakers.

A system for detecting and preventing animal intrusions was created by Shivam *et. al.* (2021). The project's main goal was to detect animals wandering into farmlands or human habitation. The methodology comprised employing diverse sensors to identify the existence of these animals near agricultural

fields or populated areas. These sensors include ultrasonic and infrared ones. In addition, an LCD is used to display messages, and a camera module takes pictures of animals. The Arduino Uno microcontroller makes it easier to integrate these components, and the intended goal was met.

An intrusion detection system was created by Shivhare *et al.* (2022) utilizing a deep learning methodology. The study offered a novel strategy to improve intrusion detection. This method combined a support vector machine (SVM), a long short-term memory (LSTM) module, and CNN. The findings indicated that CNN had an accuracy of 91.65%, CNN-LSTM had an accuracy of 93.61%, DNN had an accuracy of 95.61%, and CNN-LSTM.SVM (the proposed model) had an accuracy of 97.29%, KNN had an accuracy of 90.1%, Random Forest had an accuracy of 88.48%, and CNN had an accuracy of 91.65%.

Using a machine learning technique Suk-Ju *et al.* (2019) used unmanned aerial vehicle imagery in deep learning for bird detection. Unmanned aerial vehicles (UAVs) and aerial photography were used to train these models. The dataset was made up of a variety of photos showing birds in various environments, including farms and lakes. To increase the variety of bird patterns and boost detection accuracy, pictures of bird decoys were also added. The results of the experimental tests indicate that the trained models perform quite satisfactorily in terms of bird detection; during the testing phase, the Average Precision (AP) values ranged from 85.01% to 95.44%.

More so, Ashokkumar *et al.* (2023) integrated various components, including a Raspberry Pi as a central processing unit, cloud storage for efficient data management, and a GSM module for instant alert generation in animal monitoring. They used a comprehensive and diverse well annotated animal dataset that enabled the CNN algorithm to accurately

identify and classify animals. By integrating the CNN algorithm, IoT, Raspberry Pi, cloud storage, and GSM module, a comprehensive and robust framework for real-time detection and prevention of animal intrusion was formed. The system's ability to swiftly identify and alert farmers and authorities about potential threats minimizes crop damage, ensures human safety, and significantly reduces financial burden on the farmers.

To automate Bird Detection Based on Webcam Captured Images. Mirugwe *et al.* (2022) created a machine-learning model. The main objective of the study was to evaluate the ability of state-of-the-art deep learning architectures to recognize birds in webcam images. Faster R-CNN and the single-shot detector (SSD) were the two CNN object detectors used. Transfer learning was used, and the models used pre-trained weights from the Tensor Flow 2 object detection API and the MS COCO (Microsoft Common Objects in Context) dataset. When paired with ResNet152, the Faster R-CNN model was the most successful of these models, achieving a mean average precision of 92.3%.

A machine-learning approach was suggested by Mirugwe *et al.* (2022) to identify animals in agricultural areas. The camera used in this project is used to record the entire farm's surroundings by monitoring the entire area at regular intervals. The machine learning model was made to recognize when an animal approached the farm and to produce the appropriate sound to scare away the animal.

Existing work had some limitations, including but not limited to the inability to differentiate authorized entrants from unauthorized ones. Most of them dealt with animals only and ignored the high negative impact of human intruders. Also, the animals were not enough to cover the large percentage of predators that can prey on domesticated birds. That is, many rely on small, region-specific datasets, limiting

generalizability whereas CNN-Based Systems require large, diverse datasets for accurate detection. Traditional motion sensors and threshold-based approaches often misclassify non-threats (e.g., wind, shadows) and struggle with environmental variations (e.g., lighting, background clutter) that cause misclassification. More so many existing Systems use rule-based or simple computer vision techniques that lack real-time efficiency. Some are designed for specific species (e.g., elephants in farms, deer in roadways) and fail with unfamiliar species. More importantly

adverse weather and environmental conditions reducing detection accuracy. It is these research gaps that these researches seek to fill. Figure 1 shows the architecture of the proposed system. The details of each of the phases is described in methodology.

2.0 Materials and Methods

The flow chart in Figure 1 shows the sequences of the methodology adopted in this study.

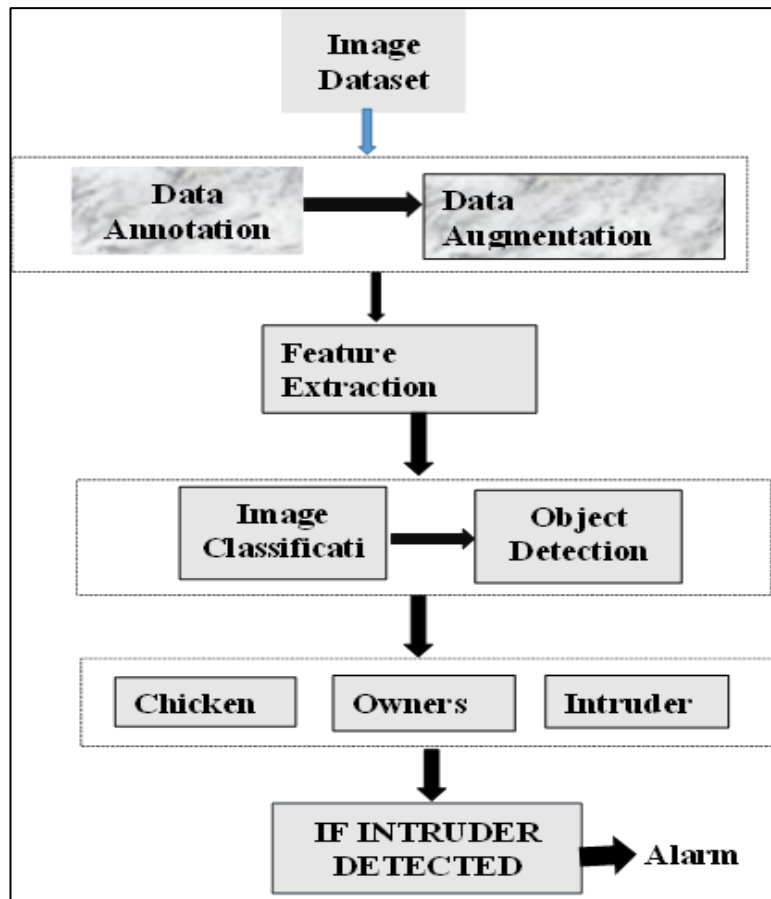


Fig. 1: Architecture of Poultry Intrusion Detection System

2.1 Data Collection

Machine learning approaches thrive on high-volume and high-quality without which, even the best machine learning algorithms cannot perform well (Whang *et. al.*, 2023). The image datasets include dogs, cats, horses, elephants, spiders, butterflies, snakes, and various other

animals and reptiles that were collected. Poultry owners and authorized workers were also added. More so, some of the images were taken from kaggle.com, an online data repository, and these images were categorized into different classes.

2.2 Data Pre-processing

The photos were cropped into the desired size. Since a substantial amount of data must be fed into the machine learning model, the datasets were expanded and enhanced using various augmentation techniques, such as flips,

brightness variations, etc. The datasets were annotated afterward; bounding boxes were drawn around each object, and the correct labels were assigned to all the images before saving them in the desired format. Figure 2 shows a cross-section of the dataset.

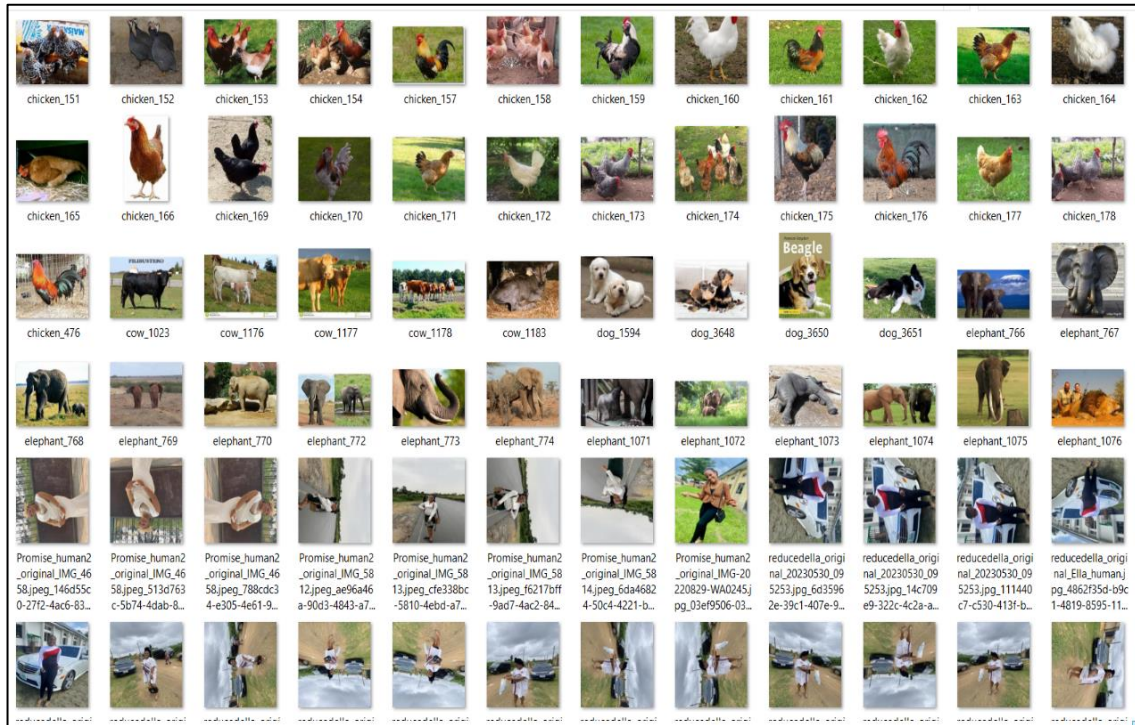


Fig. 2: Cross Section of the Image Dataset

2.3 Feature extraction

Features that are pertinent to the intrusion detection task were extracted from the pre-processed data. The size, shape, and colour of the chickens, the owner of the poultry, and other animals are a few examples of needed features.

2.4 Model selection

In this phase, the CNN architecture is designed for the task of enumeration or intrusion detection, and it was deemed appropriate. Convolutional, pooling, and fully connected layers are the standard building blocks of CNN architectures. It works well for both object detection and image classification. The YOLOv8 model which is built from CNN was used for the detection.

2.5 Model Training and Testing

PyTorch is used to build the model with the Keras library. After annotation which included drawing bounded boxes and labeling using CVAT.ai, the YOLO format which has the labels and the box dimension was exported. 80% of the photos and labels in the dataset were used for training and the remaining 20% were for testing when classifiers are being trained. This aids in evaluating the model's effectiveness. A machine learning model's robustness, validity, and dependability can be evaluated using performance and accuracy metrics. Training various models, using each on a set of data that has been set aside, and evaluating the model's performance were steps in the modeling process. Occasionally, a different test dataset from the training and validation sets is used to predict how the selected model will perform on new data.

2.6 Model Deployment

After testing, the model was deployed. This was done to attain the process's end goal.

Steps to Solve the Problem:

- i. Train the algorithm to identify different types of intruders, such as humans and predators.
- ii. Develop a CNN-based model that can accurately and efficiently detect intruders in poultry farms.
- iii. Evaluate the performance of the algorithm under different conditions, such as varying lighting conditions, weather conditions, and camera angles

The proposed system employs YOLOv8, an advanced version of YOLO based on convolutional neural networks for improved accuracy in image classification and object recognition. It detects not only animal intruders but also any unauthorized individuals other than the poultry owner. Additionally, the system performs real-time intrusion detection.

2.7 Convolutional Neural Network (CNN)

Convolutional neural networks are synthetic neural networks that, in addition to fully connected layers, also contain one or more convolutional layers (Ekong, 2023).

According to James *et al.* (2024), the previously mentioned nodes and activation

functions process the data obtained from the input layer. Each node in the input layer is directly connected to every node in the first hidden layer. Similarly, each node in the first hidden layer is connected to every node in the second hidden layer, and this pattern continues until the final layer of the neural network. The output layer, which serves as the network's last stage, is responsible for the final processing of the information and delivering the results to the user.

Convolutional layers play a crucial role in extracting key features from the input tensor's data. The primary stages of a convolutional neural network (CNN) are illustrated in Figure 3, along with a hypothetical configuration.

2.8 Convolutional Layer

This layer applies a convolution operation using a kernel on the input data. Suppose the kernel size for a single-layer image is 3×3 pixels, meaning the filter covers an area of the same dimensions over the image. The convolution process begins by applying the Equation (i) at each position.

$$\text{conv} = \sum_{i=1}^n \sum_{j=1}^m K_{ij} I_{ij} \quad (i)$$

where I represent the kernel's elements, and K describes the image area covered by the kernel.

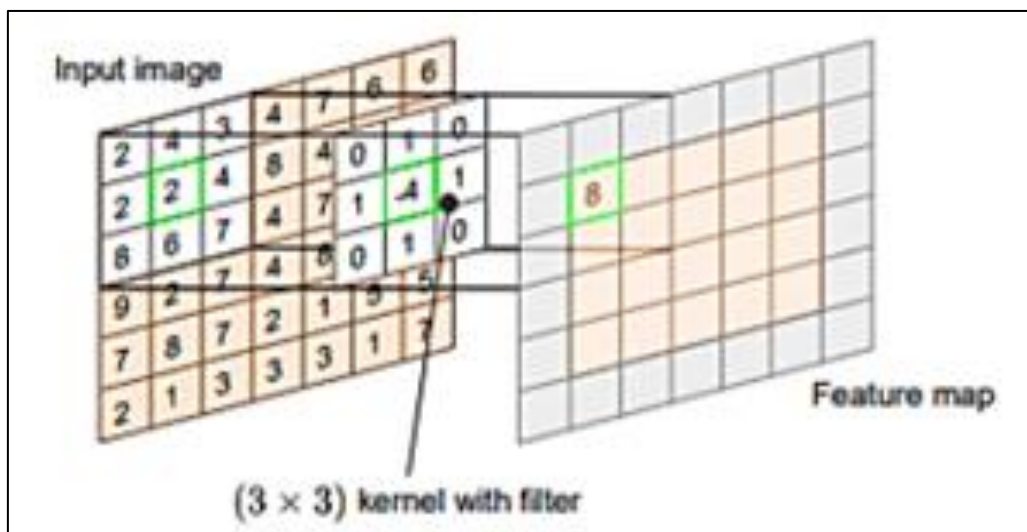


Fig. 3: The Feature Map (James *et al.*, 2024)

The convolution finishes when the kernel passes over all the tensor positions. Figure 3 shows the creation of a new output tensor known as the feature map, which contains the image's features by the kernel and image convolution.

8.1 Convolutional matrix

The max pooling selected for each input and output element could be expressed in the matrix as shown in Equations (ii)

$$\text{vec } y = S(x)\text{vec } x \quad (ii)$$

where $\text{vec } x$ represents the input vector which is the input feature map and in this case, the images or an intermediate representation; $S(x)$ represents the transformation function; $\text{vec } y$ represents the output vector, which is the transformed feature map after applying the operation $S(x)$.

2.8.2 Rectified Linear Unit (ReLU)

The ReLU's introduced non-linearity activation function in our ConvNet. Because the real-world data would want the network to learn with a non-negative linear value, hence, the need for ReLU Function. It is defined as:

$f(x) = \max(0, x)$. Here,

- If $x > 0$, the function outputs x (i.e., it remains unchanged).
- If $x \leq 0$, the function outputs 0 .

2.8.3 Softmax

The Softmax function is an activation function that was used in the output layer of the multi-class classification. It converts raw scores (logits) into probabilities by ensuring that:

- The output values are between 0 and 1.
- The sum of all output probabilities equals 1.

For a given input vector $z = (z_1, z_2, \dots, z_n)$, the softmax function computes the probability for each class i as:

$$\sigma(z_i) = \frac{e^{z_i}}{\sum_{j=1}^n e^{z_j}} \quad (iii)$$

where e^{z_i} is the exponential of the input z_i

$\sum_{j=1}^n e^{z_j}$ is the sum of exponentials of all input values. $\sigma(z_i)$ is the probability of class i .

3.8.2 CNN steps used in the intrusion detection system

- Apply **convolutional filters (kernels) to the input image** to extract spatial features and create feature maps.
- Apply a non-linear activation, RELU (Rectified Linear Unit), to introduce non-linearity function to the output of the convolutional layer.
- Perform pooling (down sampling) to reduce the dimensionality of the feature maps while retaining important information.
- Use fully connected layers to transform extracted features into a final decision-making process or connects every neuron in the previous layer to every neuron in the next layer.
- Apply the activation function** to obtain class probabilities

2.9 Algorithm

Step 1: Upload images

Step 2: Start (Convolutional Neural network) model

Step 3: Input dataset;

Step 3: Annotate the dataset.

Step 4: Split the dataset into testing and training sets

Step 5: if intruder_detected=" True":

Step 6: Alert.send_alert("intruder detected in restricted area!")

Step 7: else: Go to line 2.

2.10 Use Case Diagram

Use Case diagram, shown in figure 4, is used to visually represent the interactions among the system, external systems, and users. The usecase diagram aims to provide a visual representation of the functional requirements of a system, illustrating the connection between an actor and the crucial processes.

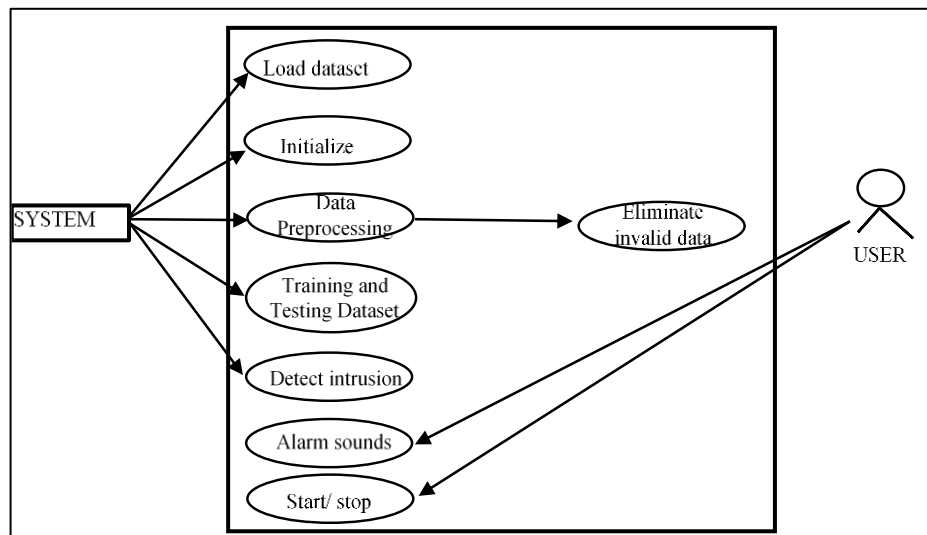


Fig. 4: Use Case Diagram of the Poultry Intrusion System

3.0 Results and Discussion

The outcomes of the Convolutional Neural Network (CNN)-based model for intrusion detection in poultry farms are the ensuing paragraphs of this section. The results are analyzed to evaluate the model's performance in detecting and classifying intrusions, considering key metrics such as accuracy, precision, recall, and F1-score. Additionally, the discussion interprets these findings and highlights the implications for real-world deployment in poultry farm security. Figure 5 is the model's confidence curve. It illustrates the model's performance by showing the relationship between its confidence in predictions and the accuracy of those predictions, as measured by the F1 score. It combines the model's certainty (confidence)

with its ability to make accurate predictions (F1 score).

Figure 6 is the models Precision-recall Curve. Recall (also known as sensitivity or the true positive rate) measures how well the classifier identifies positive instances. It's particularly useful in scenarios where identifying all positive cases is important.

The formula for recall is:

$$\text{Recall} = \text{TP}/(\text{TP} + \text{FN}) \quad (\text{iv})$$

where True Positives (TP): The number of positive instances correctly identified by the classifier.

False Negatives (FN): The number of positive instances that were incorrectly classified as negative by the classifier.

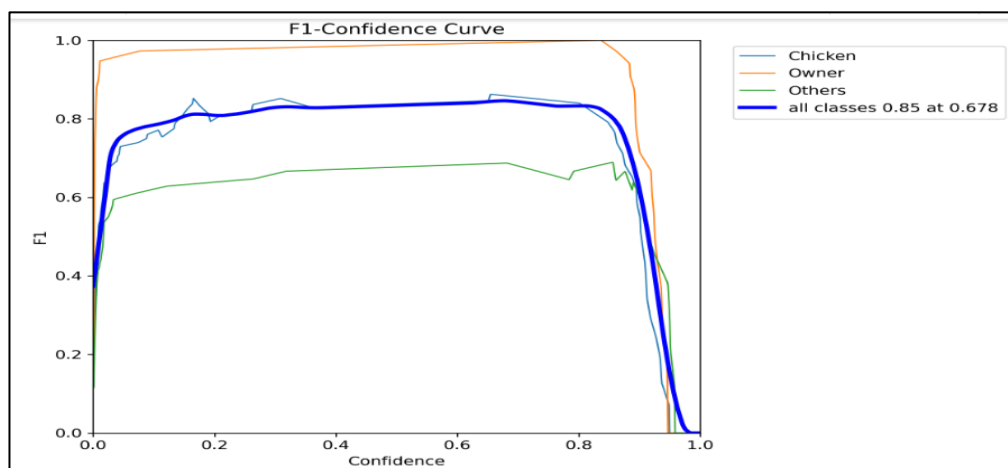


Fig. 5: F1 Confidence Curve

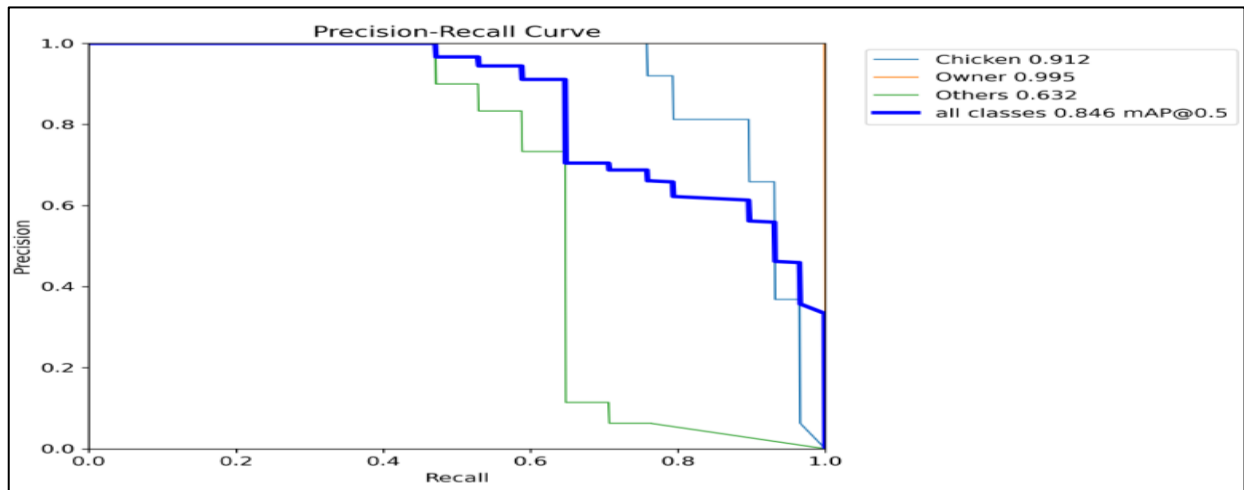


Fig. 6: Precision-Recall Curve

This curve shows how well the model identifies the objects (recall) while considering how many of the detected objects are actually correct (precision). As recall increases, precision is calculated for each threshold until the model reaches an optimal balance of correct predictions. After reaching this balance, the precision may decrease. Precision (R), also known as positive predictive value, is a metric used in classification problems to measure the proportion of instances predicted as positive

that are actually positive. It is calculated as R using FP (False positive):

$$R = TP / (TP + FP) \quad (v)$$

Similarly, figure 8 is the recall-confidence curve. It shows how frequently the model correctly identifies all the positive instances (such as chicken and owner) and how this accuracy changes with the model's confidence. The curve drops as it reaches the average rate of correct predictions.

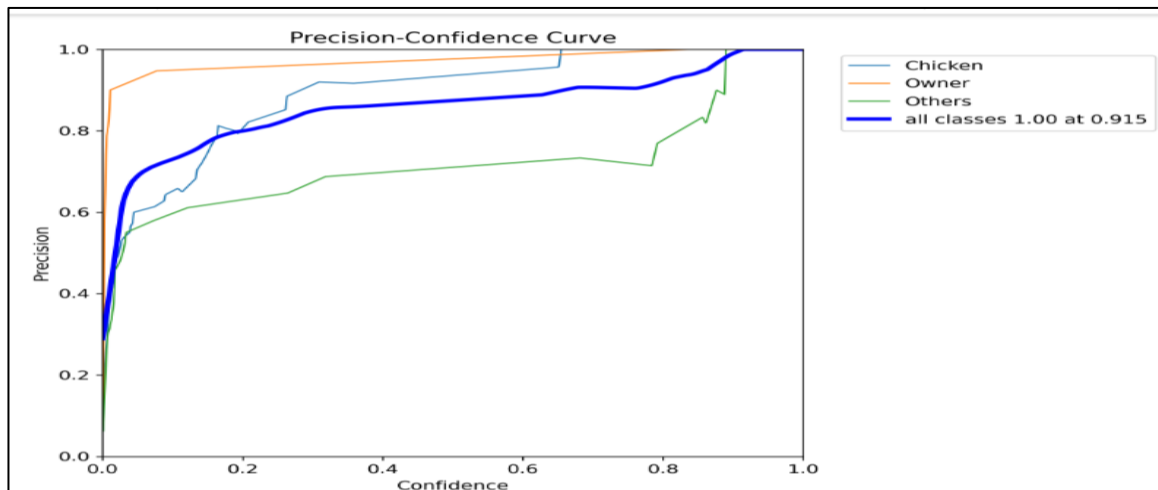


Fig. 7: Precision-Confidence Curve

Data visualization enables us to analyze data, even when we are unsure of the precise questions (Mirugwe *et al.*, 2022). Figure 9 is an illustration of the training and validation performances. It provides a visual summary of the model's performance, featuring different types of graphs that illustrate metrics such as

accuracy, precision, and recall, offering an overall picture of the model's effectiveness. X-axis (Horizontal Axis) represents training epochs (full pass through of the entire training dataset) while Y-axis (Vertical Axis) represents the bounding box regression loss, which quantifies how far off the predicted

boxes are from the ground-truth boxes. The first five graphs represent the training loss accuracy, precision and recall while the last five graphs in the same figure 9 show the validation accuracy and mean average precision as the training progresses. As the

training accuracy increases, the loss decreases for both the training and validation processes. Additionally, as accuracy improves, the model's ability to correctly predict (precision) also increases.

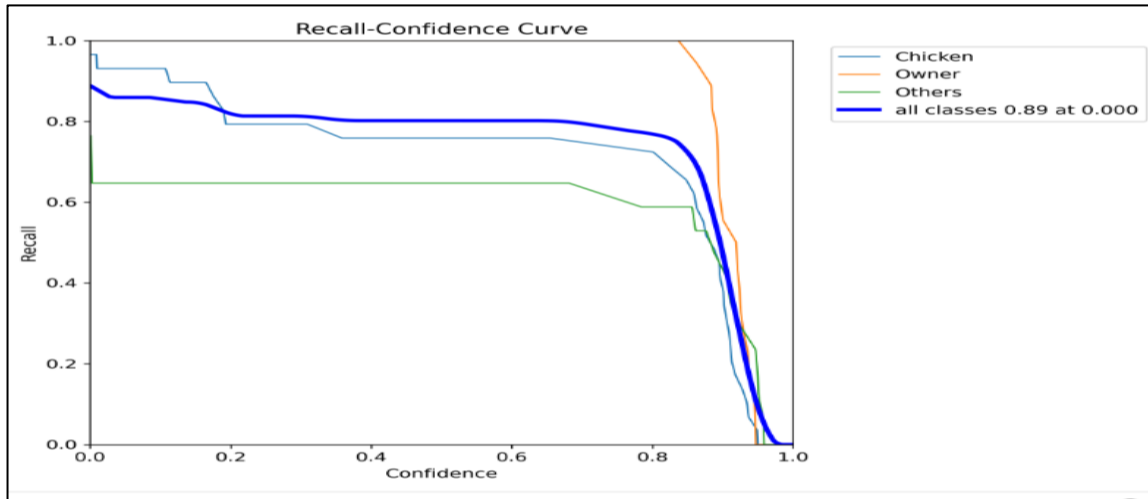


Fig. 8: Recall-confidence Curve

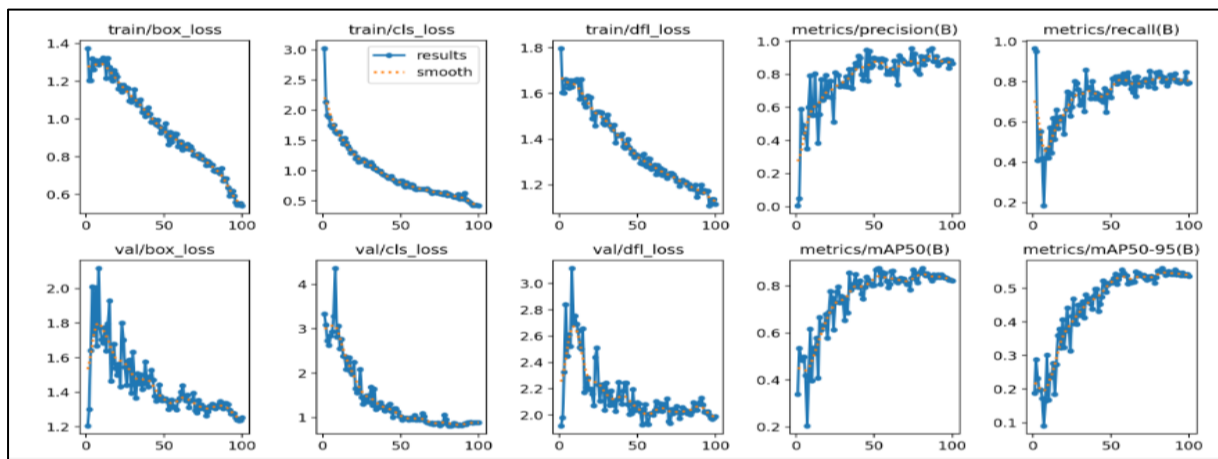


Fig. 9: Illustration of the training and validation performances

In the dataset, images are classified as false positives or false negatives when misclassified, and as true positives or true negatives when correctly identified. Several techniques were employed to evaluate the effectiveness and correctness of the model.

i. **Accuracy:** The proportion of cases that were accurately predicted to all instances. It serves as a gauge for the accuracy of the model. It is expressed as;

$$\text{Accuracy} = (\text{TP} + \text{TN}) / (\text{TP} + \text{TN} + \text{FP} + \text{FN}) \quad (\text{vi})$$

ii. **Precision:** It measures how many of the positively predicted instances are actually **correct** and is expressed as;

$$\text{Precision} = \text{TP} / (\text{TP} + \text{FP}) \quad (\text{vii})$$

iii. **Recall (Sensitivity or True Positive Rate):** The proportion of all observations in the actual class that were accurately predicted as positive.

iv. **Confusion Matrix:** A table that shows how well a classification model performs, which gives a thorough explanation of the right and wrong forecasts.

Figure 10 and figure 11 illustrates the intrusion detection model on implementation. They show how the different classes within view were classified. Figure 12 shows the confusion matrices for each of the three models that were assessed using the test dataset. In the confusion matrix, each row represents the actual review label, while each column represents the classified review label. The diagonal cell here shows the true positives meaning that 25, 16, and 11 were correctly classified as chicken,

owner, and others respectively. It also shows that two backgrounds with chicken species were correctly predicted. In the top row which is the chicken row, the model correctly labeled 25 (out of all 27) chicken images. In the second row, the model correctly labeled 16 (out of 16) owner reviews, it didn't misclassify here. In the third row, the model correctly predicted 11 (out of 12) other reviews.



Fig. 10: Object detection on implementation



Fig. 11: Object detection on implementation showing owner and chicken

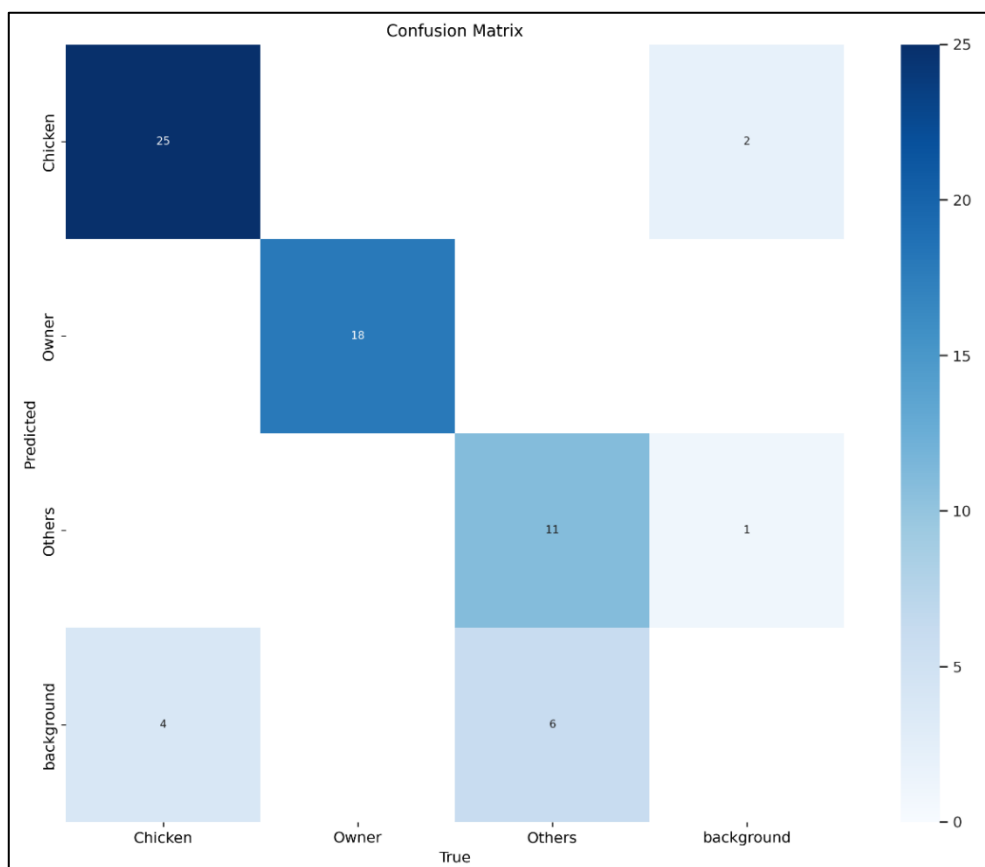


Fig. 12: Confusion Matrix

4.0 Conclusion

This research presents an innovative approach for enhancing intrusion detection systems in poultry farms through the utilization of Convolutional Neural Networks (CNNs). Intrusion detection in agricultural settings, particularly in poultry farms, poses unique challenges due to the vast and dynamic environment. Traditional intrusion detection systems often struggle to adapt to the complexities of these environments. The proposed model leverages the capabilities of CNNs, which have demonstrated remarkable performance in various image-processing tasks, to detect and classify intrusions effectively. By utilizing CNN architecture, the model is capable of learning discriminative features from image data captured by surveillance cameras deployed across the poultry farm. Key components of the enhanced model include data preprocessing techniques to enhance the quality and relevance of input images, followed by a CNN architecture

optimized for intrusion detection tasks. The CNN is trained on a large dataset of annotated images, encompassing various intrusion scenarios encountered in poultry farms. This research marks a significant milestone in the domain of agricultural security. By leveraging the power of machine learning and tailoring it to the unique challenges of poultry farm environments, the study presents a robust and effective solution for detecting intrusions. Through extensive experimentation and evaluation, the proposed model demonstrates remarkable accuracy in identifying potential threats. This enhanced accuracy is a testament to the model's ability to learn discriminative features from annotated image data, thereby improving its adaptability to the dynamic conditions of poultry farms.

5.0 Contribution/Area of Application of the Work

This research represents a significant advancement in the field of agricultural security by introducing an innovative solution

tailored specifically for poultry farm environments. The contributions of this research extend beyond theoretical advancements to practical applications, ultimately benefiting the poultry industry by enhancing security and productivity. The areas are highlighted below:

- i. Novel Application of Convolutional Neural Networks (CNNs)
- ii. Enhanced Security and Risk Mitigation
- iii. Practical Considerations for Real-world Deployment.

Conflict of interest

The author(s) declare that there are no competing interests regarding the research, authorship, or publication of this manuscript titled "Convolutional Neural Network-based Model for Intrusion Detection in Poultry Farms".

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