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Original Research Article

Real-Time Infection Detection System in Broiler Farm using MobileNetSSD Model

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KEYWORDS

Poultry farm,
Infection detection,
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Real-time monitoring,
Deep learning.

ABSTRACT

The early detection of diseases in poultry farms is very important in safeguarding flock health and reducing economic losses. Outdated method of monitoring poultry health involves manual examinations, which are time consuming, labor-intensive and prone to inaccuracies. To curtail these challenges, this study presents a real-time infection detection system using lightweight object detection model called MobileNetSSD model for efficient and automated health monitoring. The system consists of deep learning techniques with affordable hardware that support real-time detection, tracking and analysis of broilers movement patterns in farm A, that consist of untagged healthy broilers and Red tagged sick broilers. The exercise was repeated three times to obtain movement threshold 84.9cm for sick broilers and 213.03cm healthy broilers, the outcome produced from reference farm A was used to analyze farm B and farm C. The model achieved 87% average accuracy, 93% average precision 78% average recall and 84.9% average F1 score. The integration of this system into existing farms, can lead to prompt interventions, curb the spread of infections and overall improvement in health management of broilers. This also research highlights the potential of computer vision in modifying poultry health monitoring practices, contributing to more sustainable and efficient poultry farming.

CITATION

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INTRODUCTION

Poultry farming is a flourishing sector of the global food supply, with broiler birds being one of the most commonly raised and consumed poultry products(Teddy et al. 2019; Okinda et al. 2019). Yet, maintaining the health and comfort of broilers in commercial scale offers significant challenges, mostly in the early detection and control of infectious (Bao et al. 2021; Kayabaşi 2022). Infection diseases not only threaten the health of individual birds but can quickly spread across entire flocks, which can easily cause substantial economic losses(Hammad et al. 2022; Singh 2020; Mehta et al. 2022; Machuve et al. 2018). Old methods of health monitoring in poultry farms depend on manual examinations and observational skills, which are often labor-intensive, and ineffective for commercial scale farms(Okinda et al. 2019; Zhang et al. 2017). The improvement in artificial intelligence (AI) and computer vision offer prospects to modernize poultry health monitoring(Zhuang and Zhang 2019; Neethirajan 2022). Among these improvements, deep learning based models such as MobileNetSSD present real-time, automated detection abilities that can significantly improve the accuracy and efficiency of health assessments in poultry farms(Zhuang et al. 2018; Mathurabai et al. 2022). The MobileNetSSD model, identified for its lightweight architecture and high performance, is particularly suited for environments where computational resources are limited, making it ideal for deployment in agricultural settings(Mathurabai et al. 2022; Meng et al. 2022).

This research presents a real-time infection detection system that depend on the MobileNetSSD model to investigate movement patterns of broilers. Variations in movement patterns of healthy and sick broilers, those birds with less movement activities, lethargy, or erratic movements, are early indicators of potential infections(Okinda et al. 2019; Jos and Mart 2022; Younis and Hai 2022). By continuously monitoring and analyzing movement patterns, the system can offer timely alerts to farm operators, enabling faster interventions and reducing the risk of widespread disease outbreaks. The integration of such a system can improve flock management, reduce mortality rates, and enhance the overall productivity of poultry farms through continuous, real-time health monitoring.

MATERIALS AND METHODS

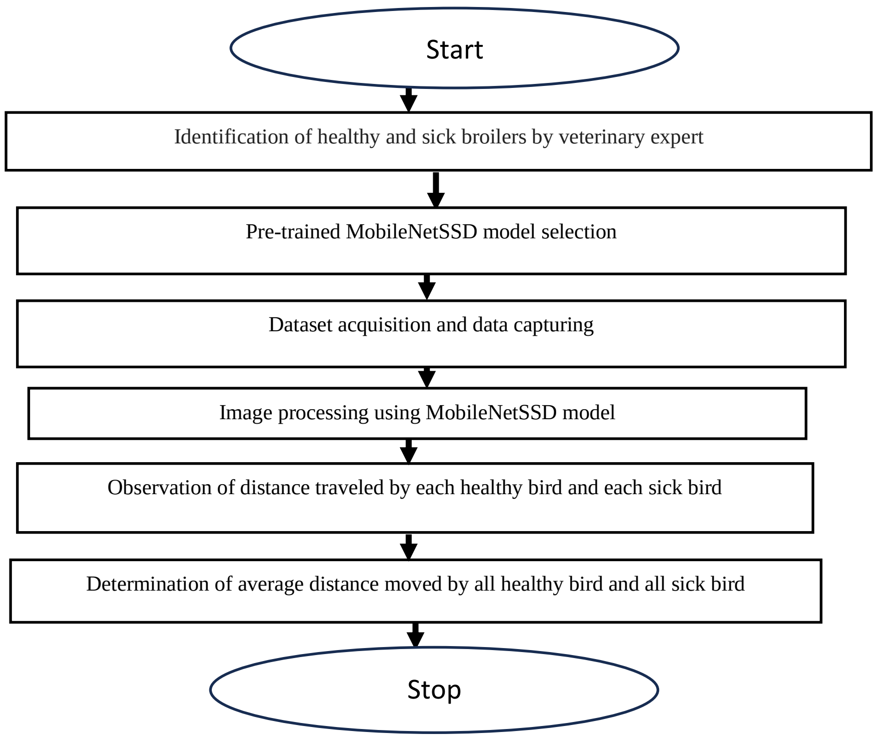

Figure 1: Workflow adopted in the research

This segment provides the approach taken to develop and implement a real-time infection detection system using the MobileNetSSD model to analyze the movement patterns of broilers. The methodology useded in this research is shown in figure 1. This starts with identification of healthy and sick broilers by veterinary expert then followed strictly with data acquisition. Afterwards, the data is processed and analyzed. Adaptation of MobileNetSSD model for object tracking and detection. With the application developed, the distance moved by birds are observed to determine the average distance moved by healthy birds and sick birds. Afterwards, the average distance threshold is determined.

Identification of healthy and sick broilers by veterinary expert

Assistance of expert from ministry of livestock and fisheries Niger state Minna, to identify healthy and sick broilers before and after each experiment in farm A, farm B and farm C. The sick broilers identified by the expert are tagged with red ribbon tied to their wings while the healthy broilers are not having any tag ribbon, as shown in figure 2. Features of sick broilers was further explained such as decreased appetite, weakness, gasping for air, reluctance to move, feather loss and discharges from eyes and nostrils.

Figure 2: Groups of healthy and sick broilers

Pre-trained MobileNetSSD selection

The pre-trained MobileNetSSD model is a model which has been trained to identify general features from a standard dataset, such as ImageNet or Common Objects in context dataset (COCO dataset)(Robotics 2021). The model was further fine-tuned to identity birds in the farm. Selecting this model is very important for several reasons, particularly in applications like object detection in resource constrained environments: Speed, Accuracy and Versatility. Furthermore, selecting a pre-trained MobileNetSSD model lies in its balance between performance and efficiency, ease of transfer learning, and suitability for deployment in real-world, resource-constrained environments(Younis and Hai 2022).

Dataset acquisition and data capturing

The datasets used in this research is SSD_Mobilenet_v3_large_coco_2020_01_14.pbtxt usually called COCO dataset, download from https://gist.github.com. The dataset which is well structured and used for object detection in different computer vision studies, contain eighty (80) object classes and 328,000 images in each object class. To be adoptable in this research, certain adjustment had to be done. This includes:

Subset Selection

In the quest to reduce complexity, the COCO dataset which has a wide range of object classes had to be modified. This is necessary so as to achieve the detection of object of interest which is a bird. To achieve this, a subset was created of the dataset that contain only the related object class.

Aside the above mentioned procedure, new data is captured using a web camera. The image captured by this camera is then broken down into frames after which it is processed for tracking and detection. The dataset was used to train the system to identify birds only irrespective of their health status.

Data Processing

This process involves the formatting of the data so that it could be useful for the model intended to be used. The process used in the data processing includes:

Augmentation

This involves techniques like random scaling, rotations, brightness adjustments, and horizontal flips to improve the model's robustness and generalization.

Image Resizing

Due to the fact that the MobileNet-SSD model frequently expect input images of 600x600 pixel, the input images are resized for compatibility.

Non-Maximum Suppression (NMS) Threshold

In the quest to lessen the number of overlapping boundary boxes after detection, NMS threshold was adjusted. A lesser threshold will keep more boxes, while a higher threshold will eliminate more duplicates. For optimum performance, the threshold was set at 0.3.

Confidence Threshold

To screen out low-confidence detections, confidence threshold for object detection is set at 0.5. Therefore, only objects with confidence scores of 0.5 and above threshold are considered valid for detection.

Step wise activities in image processing using MobileNetSSD model

MobileNetSSD model is generally known for its ability to balance accuracy and speed, making it ideal for real-time applications(Robotics 2021; Rajora et al. 2022; Chiu et al. 2020; Muwardi et al. 2023). The whole system start with importing relevant libraries like cv2, numpy, math and time. Loading pre-trained MobileNetSSD model weights and configuration file using deep learning framework(Younis and Hai 2022 ; Meng et al. 2022) Since we are not training MobileNetSSD model from scratch, then the following files need to be download first to our working directory. Caffe prototxt file: the file contain the model definition which is the convolutional Architecture for fast feature embedding. Caffe model file: the file contains pre-trained model weights.Pre-trained MobileNetSSD model operates as follows:

- **Input Image/Video**: The model takes an input image or video frame, typically in RGB format, and processes it through the MobileNet base network.
- **Feature Extraction**: The pre-trained MobileNet layers extract relevant features from the input, focusing on edges, textures, and other visual cues that might indicate objects of interest (e.g broilers).
- **Object Detection**: The SSD detection object, fine-tuned for the specific task, uses these features to predict bounding boxes around detected objects and with x and y coordinates of each detected object.
- **Object Tracking**: In the first frame after detection, a bounding box drown around each detected object. The program generates identification (id) number to each bounding box and computes the centroid of each bounding box using x and y coordinates of the box. All these happened in the first frame. Now moving to the second frame, the tracking techniques relies on Euclidean and computes distance between every pairs of centroids in the frame. Certain minimum distance move is assumed, if an object movement is within the minimum distance that object compare to other frame and is said to be the same object but if the movement is more than minimum distance, new id is assign to the object as a new object. Moving to third frame which the new frame while the second frame is old frame Euclidean computes the distance again to either detect the same object or new object in the frame. Furthermore, the system also computes all the movement of each broiler and compare to determine the broilers with less movement.
- **Output**: The model outputs a list of detected objects, each with a bounding box, a confidence score, and a class label. This output can be used for further analysis or real-time decision-making,

Observation of distance covered by healthy and sick broilers

To be able to determine the threshold of maximum distance that was travel by a broiler in one hour, each broiler was monitored using MobileNetSSD model and each bird was observed to known the average distance covered every one hour. The experiment was performed three times in the reference farm A.

Determination of average distance moved by all healthy bird and all sick bird

Each broiler was observed using the MobileNetSSD model at an interval of 1 hour for 5 hours. The distance moved by each bird was computed using distance formula, also known as the Euclidean distance formula:

Distance (D) = $\sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$ (1)

This formula gives you the straight-line distance between two points in a two-dimensional Cartesian coordinate system(Rajora et al. 2022). Where D is the numeric value of the distance and i is the position of the bird at that point in time. Afterwards, to calculate the distance between a series of coordinates, you can iterate through each pair of consecutive points and sum up the distances and also find the average distance covered by each bird is given as

Total D moved by each bird = $\sum_{i=1}^{n-1} \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$ (2)

Average D moved by each bird

$= \frac{\sum_{i=1}^{n-1} \sqrt{(x_2-x_1)^2+(y_2-y_1)^2}}{5}$ (3)

The cumulative distances between each point and the starting point, the total distance moved by all the birds in this experiment is given as

Total distance coved by all birds = $\sum_{j=1}^{i} \sqrt{(x_j - x_{j-1})^2 + (y_j - y_{j-1})^2}$ (4)

Average distance coved by all birds =

$\frac{\sum_{j=1}^{i} \sqrt{(x_j-x_{j-1})^2+(y_j-y_{j-1})^2}}{10}$ (5)

Healthy birds and sick birds were handpicked by a certified veterinary doctor. The sick birds were then tagged with red ribbon tied to their wings. Afterwards, both the healthy and sick birds were mixed in the experimental space to test the MobileNetSSD application. The sick ones were identified via the use of red bounding boxes while the healthy ones were identified via the used of green boundary boxes.

Metrics for Evaluation of MobileNetSSD Model

The MobileNetSSD model was used to detect and tracked all broilers within confirmed environment. However, the accuracy of detection was measured using confusion metrics and the following metrics:

i. Accuracy = $\frac{(TP+TN)}{(TP+TN+FP+FN)}$ (6)

ii. Precision = $\frac{TP}{TP+FP}$ (7)

iii. Recall = $\frac{TP}{TP+FN}$ (8)

iv. F1 Score = $\frac{2*Precision*Recall}{Precision+Recall}$ (9)

In the above equations 6 to 9, True Positive (TP) is numbers of correctly identified sick broilers, False Positive (FP) is the numbers of non-sick broilers but predicted sick, True Negative (TN) is the numbers of non-sick and predicted as not sick while False Negative (FN) is numbers of sick broilers but identify as not sick

RESULTS AND DISCUSSION

Result of the Model

The development of intelligent computer vision system for monitoring broiler birds was done and tested, the result of the system developed is shown in figure 3 to 5 for farm A, farm B and farm C. The green bounding box signified healthy broiler while red bounding box signified sick broiler.

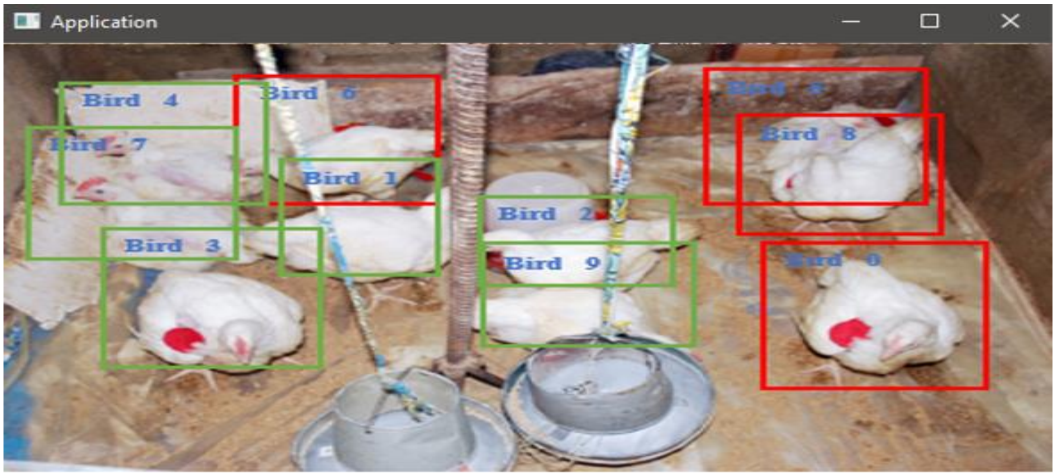

Figure 3: Results of MobileNetSSD model for tracking and detection of broilers in farm A

Figure 4: Results of MobileNetSSD model for tracking and detection of broilers in farm B

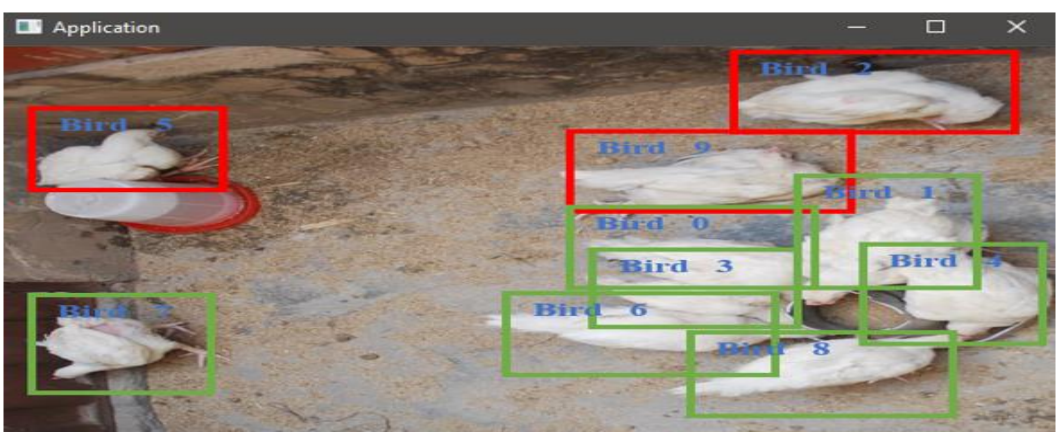

Figure 5: Results of MobileNetSSD model for tracking and detection of broilers in farm C

Farm A experiment was conducted three times, as shown in Table 1 to 3.

Table 1: First experiment in farm A

Broiler id	First hour(cm)	Second hour (cm)	Third hour(cm)	Forth hour(cm)	Fifth hour(cm)	Average (cm)	Remark
0	96.2	91.1	92.4	82.8	79.4	88.4	Sick
1	210.2	226.1	224.4	202.8	221.9	217.1	Healthy
2	233.1	230.7	243.5	227.7	238.5	234.7	Healthy
3	164.3	177.3	172.5	198.5	181.7	178.9	Healthy
4	211.8	233.6	230.7	226.2	222.5	225.0	Healthy
5	98.1	94.2	90.5	86.7	88.5	91.6	Sick
6	104.3	102.3	90.6	93.5	91.7	96.5	Sick
7	192.6	234.3	214.1	229.7	222.6	218.7	Healthy
8	99.3	98.6	95.7	91.2	87.5	94.5	Sick
9	209.7	220.9	225.2	218.4	211.4	217.1	Healthy
Total average movement covered by healthy broilers						215.3	
Total average movement covered by sick broilers						92.8	

Table 2: Second experiment in farm A

Broiler id	First hour(cm)	Second hour (cm)	Third hour(cm)	Forth hour(cm)	Fifth hour(cm)	Average (cm)	Remark
0	85.7	83.6	81.9	75.3	71.9	79.7	Sick
1	197.7	220.6	229.5	212.1	203.4	212.7	Healthy
2	218.7	200.9	214.1	211.8	210.5	211.2	Healthy
3	180.3	155.4	177.5	187.5	185.3	177.2	Healthy
4	196.7	218.4	225.3	211.2	207.6	211.8	Healthy
5	90.6	83.7	85.9	79.2	73.5	82.6	Sick
6	95.3	90.3	87.0	75.5	81.2	85.9	Sick
7	208.2	219.2	222.5	209.3	225.9	217.0	Healthy
8	88.8	86.6	82.2	77.7	75.5	82.2	Sick
9	200.6	219.3	230.1	211.9	204.2	213.2	Healthy
Total average movement covered by healthy broilers						207.2	
Total average movement covered by sick broilers						82.6	

Table 3: Third experiment in farm A

Broiler id	First hour(cm)	Second hour (cm)	Third hour(cm)	Forth hour(cm)	Fifth hour(cm)	Average (cm)	Remark
0	87.2	79.1	74.4	70.8	68.9	76.1	Sick
1	207.5	220.8	233.6	224.9	225.5	222.5	Healthy
2	214.7	227.6	233.3	237.5	223.5	227.3	Healthy
3	194.0	167.3	190.2	193.7	203.1	189.7	Healthy
4	203.1	225.3	233.4	210.3	229.7	220.4	Healthy
5	83.1	80.7	78.5	77.7	73.5	78.7	Sick
6	89.3	87.3	82.5	78.5	76.7	82.9	Sick
7	212.0	229.5	218.6	224.9	226.1	222.2	Healthy
8	84.3	83.6	80.7	76.2	72.5	79.5	Sick
9	221.3	207.3	235.4	225.9	196.4	217.3	Healthy
Total average movement covered by healthy broilers						216.6	
Total average movement covered by sick broilers						79.3	

Experiment in Farm B

Similar experiment was carried out in farm B using the set threshold in farm A, the system was able to detect five sick broiler and five healthy broilers as shown in table 4

Table 4: Farm B experiment results

Broiler id	First hour(cm)	Second hour (cm)	Third hour(cm)	Forth hour(cm)	Fifth hour(cm)	Average (cm)	Remark
0	227.6	225.6	241.8	249.8	236.9	236.3	Healthy
1	109.8	103.1	94.7	89.0	90.6	97.44	Sick
2	114.6	108.5	98.6	86.0	81.0	97.7	Sick
3	252.9	230.3	202.3	231.9	241.8	231.9	Healthy
4	247.5	241.8	233.7	220.9	237.6	236.3	Healthy
5	238.9	245.1	254.1	228.8	231.9	239.8	Healthy
6	104.4	97.1	97.8	75.9	72.2	89.5	Sick
7	107.7	93.6	81.8	79.4	71.4	86.8	Sick
8	92.3	87.3	82.1	83.3	77.9	95.9	Sick
9	232.4	239.3	253.9	231.2	223.1	236.0	Healthy

Experiment in Farm C

The same experiment was carried out in farm C using the set threshold in farm A, the system was able to detect three sick and seven healthy as shown in table 5

Table 5: Farm C experiment results

Broiler id	First hour(cm)	Second hour (cm)	Third hour(cm)	Forth hour(cm)	Fifth hour(cm)	Average (cm)	Remark
0	222.2	235.8	263.5	254.9	240.5	243.4	Healthy
1	235.1	245.1	223.7	215.4	237.6	231.4	Healthy
2	109.7	92.6	98.3	87.5	81.0	93.8	Sick
3	239.0	246.8	220.2	229.7	251.1	237.4	Healthy
4	263.1	225.3	248.4	243.3	229.7	241.9	Healthy
5	103.9	97.8	102.2	92.6	81.5	95.6	Sick
6	246.6	226.1	247.2	234.3	249.6	240.8	Healthy
7	241.9	229.5	233.6	224.9	238.1	233.6	Healthy
8	226.2	231.6	250.9	234.9	241.4	237.0	Healthy
9	81.9	85.8	74.3	80.1	70.4	78.5	Sick

Discussion

As observed in figure 3 above, the intelligent system for monitoring broilers using MobileNetSSD model demonstrated remarkable performance in detection and tracking broilers in confined environment. The real time processing capability of the model allowed for efficient and swift detection, ensuring minimal latency in recognition of broilers movement. The model generated unique identification number for each broiler starting from 0 to 9 and green bounding box signified healthy state while red bounding box signified unhealthy state. As shown in table 1 to 3, it is observed that the average threshold of sick broilers is 84.9cm, while for the healthy broilers is 213.03cm.

As shown in Table 4, broiler id number 1, 2, 6, 7 and 8 exhibited significantly less movement pattern compared to their healthy counterparts which aligned with the findings of (Neethirajan 2022) and (Okinda et al. 2019). Both works stated that healthy broilers are generally more active while sick broilers are less active, and they exhibit less movement. As shown in Table 5, it is observed that broiler id number 2, 5 and 9 exhibited significantly less movement pattern compared to their healthy counterparts which aligned with (Neethirajan 2022) and (Okinda et al. 2019) finding of less active motion of sick birds.

Table 6 shows the average result of accuracy, precision, recall and F1 score in all the three farms (Farm A, farm B and Farm C) while the figure 6 is the graphical plot

Table 6: Average performance evaluation result

	Accuracy	Precision	Recall	F1 score
Farm A	0.9	1	0.8	88.89%
Farm B	0.8	0.8	0.8	80%
Farm C	0.9	1	0.75	85.71%

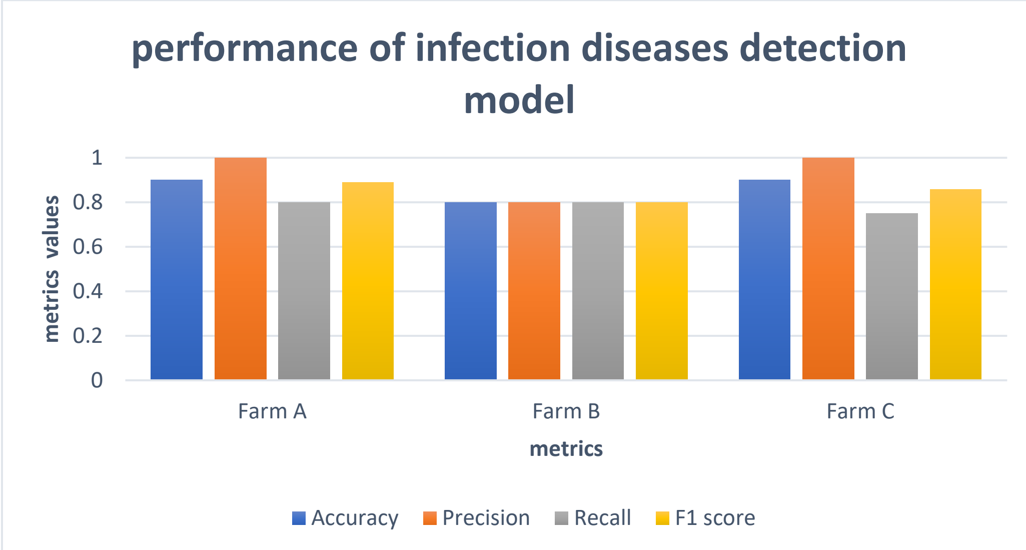

Figure 6: Performance measure of the model from all farms

From Table 6 and figure 6, MobileNetSSD model achieved an overall average accuracy of 87%, average precision 93%, average recall 78% and average F1 score 84.87%. Compared to the accuracy result of 98.8% by (Okinda et al. 2019) and mean average precision of 99.7% and 48% by (Zhuang et al. 2018), they seem to perform higher, however, they all adopted support vector machine but the model is still within useful range. The advantage of this work is the adoption of the MobileNetSSD model's lightweight architecture which ensued minimal memory usage, enabling deployment on resource constrained devices without forfeiting performance.

CONCLUSION

In conclusion, MobileNetSSD model offerings a promising style for detecting sick broilers through the analysis or calculation of movement patterns. By leveraging on deep learning techniques, this model can effectively captures nuanced features indicative of sickness, assisting in early detection of sick broilers.This study demonstrated the effectiveness of the MobileNetSSD model in detecting sick broilers through movement pattern analysis, achieving: 0.87 average accuracy, 0.93 average precision 0.78 average recall and 84.87% average F1 score. As demonstrated in three farms visited, the model unveils laudable performance in differentiating between healthy and sick broilers, showcasing its potential as a valuable tool for boosting animal welfare and farm management practices. Furthermore, constant fine-tuning and validating of this MobileNetSSD model will help in early detection and mitigation of illness in broiler populations, eventually contributing to better health outcomes and productivity within the poultry business.

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