Detection and Classification of Disease in Poultry farm

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Abstract

Poultry disease outbreaks have become more common in recent years, wreaking havoc on the poultry industry. They have not only cost farmers a lot of money, but they have also put people's health in jeopardy. As a result, chicken illness has become a major concern for poultry producers and the country as a whole. The emergence of poultry illnesses can frequently pose a major hazard to human health. Despite the large volume and intensity of chicken husbandry, poultry disease surveillance is still reliant on manual observation. The disease called Newcastle disease (NCD) causes more death of broilers in poultry. The virulent Newcastle disease virus infects domestic chickens and other bird species, causing NCD (NDV). It's a worldwide condition that usually manifests as an acute respiratory infection, but it can also express as sadness, nervousness, or diarrhoea. We construct a bespoke model based on the YOLO v3 algorithm to identify illnesses in broilers in poultry in this project. The YOLO weight file has been developed by using Darknet framework and deployment of the model is done by using Tkinter model in python. The model performs well when compared with other deep learning algorithms.

Keywords: *yolo (you only look once), Arduino uno, poultry, poultry tracking, NCD, Chicken illness, Object Detection, Multiple Box detection, Buzzer, LCD Display.*

I. Introduction

The birds are hanged by their feet during electric stunning treatments, and an electrically charged saline solution (approximately 1% NaCl) is provided to their heads, causing the current to flow through the broiler's body and reach the hook as the ground current. With the correct shock, broilers may be knocked unconscious for 60–90 seconds. The broiler is unable to stand or reposition itself when it is taken from the hook and placed on the ground at this period. The wings are squeezed against the body while a stun, and the neck is rigid. Other advantages of proper stuns include quicker bloodletting, better feather removal and less carcass damage and tender meat. Due to the fact that the broilers awaken during the slaughter, an insufficient stun might result in injuries and blood clot in the chicken wings. YOLO defined model is developed depending upon RCNN to emphasize individual variations while reducing the effect

of the same area of the picture on identification part. The YOLO algorithm is trained to detect the stunned condition of broiler chicks using an image dataset including three kinds of stunned state (insufficient, suitable, and excessive stun). This research also represents a novel deep learning application situation in agriculture. The suggested approach can be used in industry because it requires little prior knowledge of picture recognition.

II. LITERATURE REVIEW

Cheng Fang et al. (2020) conducted comparative research on deep regression network-based poultry target tracking methods. Poultry tracking is mostly used to evaluate anomalous behavior in poultry and to anticipate illness [12]. Offline video is frequently used to monitor and record the behavior of chickens. Poultry, on the other hand, are animals that are kept in groups. To that purpose, this article uses computer vision technologies to show the usage of a deep regression network to track single fowl. In terms of overlap. The poultry tracking method TBroiler tracker suggested in this research surpasses the Mean Shift Module, Multitask Learning Module, Kernel Correlation and Adaptive Correlation Filters, and tracking algorithms in terms of ratio, pixel error, and failure rate. -learn-detection. TBroiler had a mixed reaction.

Unmanned Aerial Vehicles (UAVs) are rapidly being employed in surveillance and traffic monitoring because of their high mobility and ability to cover a wide range of heights and places, according to Bilel Benjdira et al., (2019). One of the most difficult tasks is to use aerial photos to reliably recognize and count automobiles in real time for traffic monitoring. For real-time classification and identification in computer vision, many deep learning algorithms based on convolution neural networks (CNN) have recently been represented. Their performance, however, is dependent on the settings in which they are utilized. This study compares the performance of two cutting edge CNN algorithms, Faster R-CNN and YOLOv3, in the context of automotive detection from aerial photographs. On a vast scale, we trained and evaluated these two models [19].

Xiaolin Zhuang and Tiemin Zhang (2019) developed a method for detecting sick broilers using digital image processing and deep learning. This study proposed a model structure to identify sick broilers in a flock using digital image processing and deep learning. [13]. The Improved Feature Fusion Single Shot MultiBox Detector (IFSSD) was created with InceptionV3 as its foundation to improve the Single Shot MultiBox Detector (SSD) model. IFSSD's structure used 1 1 convolution to change the size and dimension of the four layers in the modified InceptionV3, pairwise fused the layers to generate three layers of varying sizes, and then built a feature pyramid network. The model has a mean average precision (mAP) of 99.7% and a mean average precision (mAP) of 48.1 percent (intersection-over- union (IoU) > 0.5).

Chethan Kumar V, Punitha R (2020) suggested an object identification method for traffic and surveillance You Just Look Once apps are a type of software that allows you to look at something only (YOLOv3 and YOLO v4). A neural network is made up of an input layer, at least one hidden layer, and an output layer. Image classes such as automobile, truck, human, and two-wheeler were gathered in RGB and grayscale photos in a multiple object dataset (KITTI picture and video). Images and movies with varying amounts of light make up the collection. For image and video datasets, YOLO model variants such as YOLOv3 and YOLOv4 are implemented. According to the findings [14], the system recognizes objects with an accuracy of around 98 percent for the photo dataset and 99 percent for the video dataset.

III. DIFFERENT TYPES OF TECHNIQUES

A. Machine vision

Machine vision has become more widely employed in agricultural detection and recognition as the field of The field of computer vision and image processing has advanced. Using the following picture segmentation, feature extraction, and pattern recognition algorithms, several methods for identification and detection have been developed.

B. Computer vision

A computer vision system and backpropagation neural networks were used to identify a broiler's stunned state, and the recognition accuracy was 90.11 percent. However, the accuracy of image processing and feature extraction approaches is highly dependent on feature extraction and selection. Specifically, the startling state's features should be precisely retrieved, and relevant characteristics should be chosen. Improper extraction and selection procedures will have an impact on the recognition outcomes.

C. Deep learning

Deep learning is gaining traction as a strong module for feature and method identification that can address today's problems. Deep learning has opened up a plethora of new application possibilities for a range of industries. A multimodel data fusion technique for combining video and audio data to carry out emotional video content using deep learning was developed substantiate the need for network training the proposed method improves network information flow and is exactly same to performing equipment vibration signals with varying timing duration. The proposed approach could be used in industry because it requires little prior knowledge of defect detection and signal processing. The researchers assessed deep learning's achievements into date, medical and radiation treatment have been studied, and some of the most potential future courses have been offered, both in terms of applications and technological developments. In a number of image recognition-related activities, deep learning has also produced good results.

D. Convolutional Neural Networks

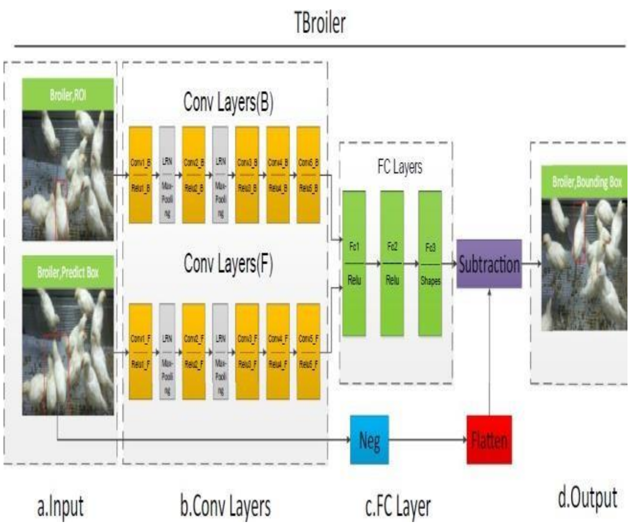
CNN is one of the most successful method for picture identification among them, with the accuracy of 96.98 percent, a CNN was created for date fruit categories. Instead of manually collecting features from training datasets, CNNs may learn the right features automatically. As a result, minimal prior experience with picture recognition is necessary, which helps to the method's industrial use. Deep learning has the disadvantage of taking longer to train, but it generally takes less time to test than other machine learning algorithms. While CNN has had a lot of success, fully training a deep model can be difficult since optimization gradients might vanish or extend during back-propagation.

IV. EXISTING METHOD

Picked 10 broiler chickens for object detecting comparison and performed three consecutive trials, each tracking a different broiler bird, to assess the broiler tracker's tracking performance. Broiler hens were picked at random for the investigation. This experiment compares the TBroiler method, the Mean Shift Module, the Multitask Learning Module, the Kernel Correlation Filter , the Adaptive Correlation Filter , and Tracking-Learning-

Detection . The architecture of the present technique is described in the section below (fig 1).

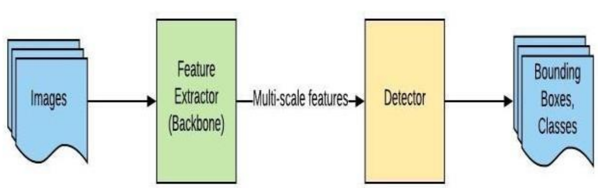
Fig. 1. Existing method for TBroiler



Frequent monitoring of broiler chicks may be accomplished by precise tracking in order to do additional analysis, which is advantageous to accurate poultry security monitoring and maintenance.

YOLOv3 recognizes this as a regression issue. It divides the picture into a ss grid, and the cell predicts bounding boxes with the confidence of those boxes, then produces final detection based on the class probability map.

Fig. 2. Existing method for Yolo Multiple Object Detection



V. PROPOSED METHOD

We train the yolo algorithm for out custom objects (fig 3). In order to train our model and generate weights file, the Darknet framework work has been used which is developed in C language. Hence, we need to perform the compilation process before train the model. Darknet is an open-source neural network framework. It is a fast and highly accurate (accuracy for custom trained model depends on training data, epochs, batch size and some other factors) framework for real time object detection (also can be used for images). The most important reason it is fast because it is written in C and CUDA and also flowchart mentioned in fig 4.

A. Collecting the images

Data collection is another important process in machine learning domain. The NCD is a disease which cause huge amount of death in broiler community in poultry forms. Hence the NCD has been trained in the proposed method to identify the NCD at broiler chickens. The Image data has been collected in third party web side which contains 500 images for both the train and testing process.

B. Labelling the images

Labelling of the image is a process which is important for the YOLO custom object detection. In this process, the LabelImg tool has been used for labelling. Labelling is process to generate a text file for an image to identify the particular object. The text file contains five in it which are number notation of class, X and Y co-ordinates. It w i l l r e p r e s e n t t h e centre of the object, and height and width of the object. Those five values used to train the YOLO model and laterally identify the objects.

C. Getting and setting up darknet

The Darknet framework work has been used which is developed in C language. Hence, we need to perform the compilation process before train the model. Darknet is an open-source neural network framework. It is a fast and highly accurate (accuracy for custom trained model depends on training data, epochs, batch size and some other factors) framework for real time object detection (also can be used for images).

D. You only look once(YOLO)

The YOLO approach, which combines the target categorization and location duty. It doesn't require a specified region, and it builds bounding box coordinates and probabilities for each class using regression, significantly speeding up detection.

The module seperates each photo in the training set into grids. The grid is in charge of detecting the target if the target ground truth's center is in a grid. Each grid identifies bounding boxes and their confidence ratings , as well as conditional probabilities of the class. For grids, the YOLO detection model finally produces a tensor of size. When the target is in the grid, (Object) equals 1; otherwise, it equals 0. The IoUpred truth is used to show that the reference and expected bounding boxes are the same. When there are items in the grid, the confidence indicates the predicted accuracy.

The real-time performance of the detecting method is critical in this case. Because of its quick detection speed, In identification and applications with real-time, the YOLOv3 module is used. YOLO + MRM is made up of convolutional, max pooling and connected layers. Down sampling procedures were performed using the max pooling layer, which included shrinking the feature maps by a factor of two in both width and height.

Fig. 3. Customized Yolo Architecture for Chicken Detection

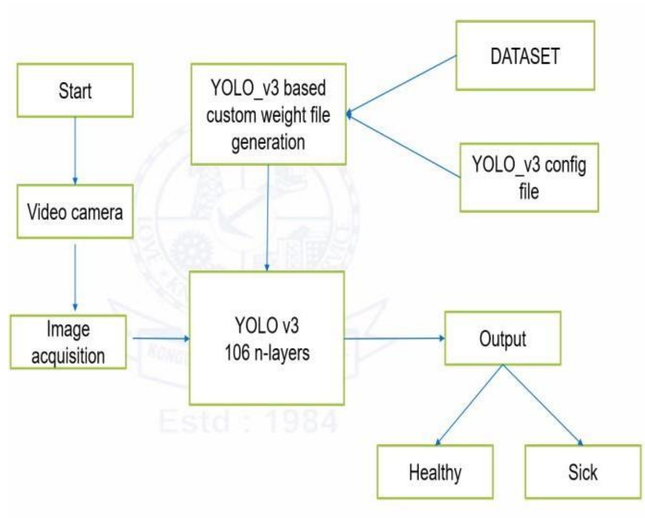


Fig. 4. Flow Chart for finding Diseases in Chicken

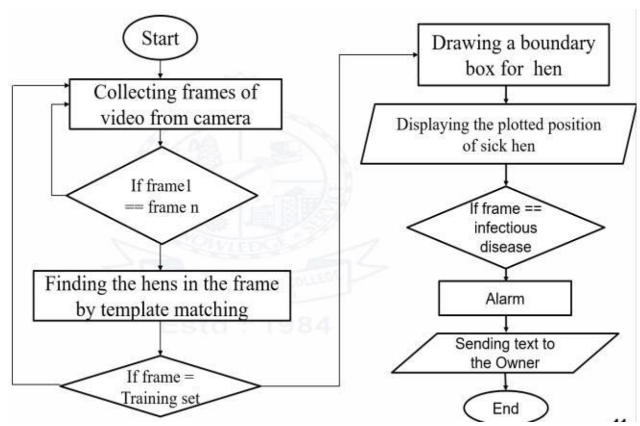
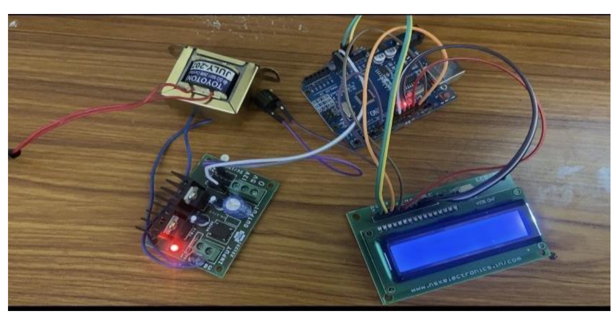


Fig. 5. Prototype Design using Arduino



The above fig.5 shows the complete prototype of the hardware setup which consists of power supply, Arduino uno, stepdown transformer for power supply, LCD Display and Buzzer.

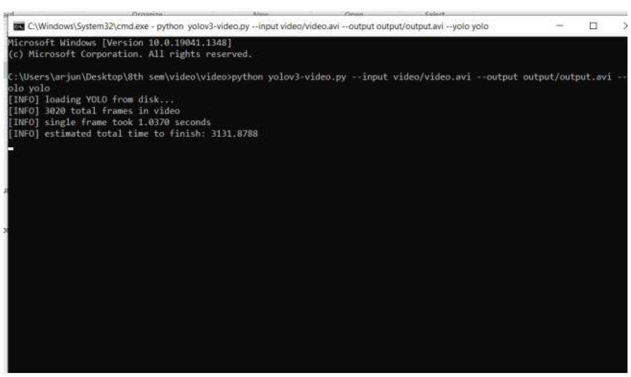
Fig. 6. LCD Display

Fig.6 is particularly about the LCD Display. LCD display is to indicate the user whether the chicken is healthy or affected by disease i.e Unhealthy.

VI. RESULTS AND DISCUSSION

Training the model with yolo using images and input of the model is video given by tester testing it using Python OpenCV. While uploading the video the parameters like total frames in video, time taken for each single frame, total estimated time are shown (fig 7) in the command window.

Fig. 7. Command Window for Testing Input Video



MODEL 1:

In model 1, the parameters such as batch, subdivision, learning rate are modified, trained using yolo, tested and output is obtained as shown in fig.8,9.

Fig. 8. Output for Healthy Chicken

Fig. 9. YOLO Configuration Changed Output for Healthy Chicken

MODEL 2:

In model 2, the parameters (batch, subdivision) changed with the use of yolo config value trained after estimated time weight file generated, that weight file replaced in model 1 weight file slot then tested output shown in fig.10,11.

Fig. 10. Output for Unhealthy Chicken

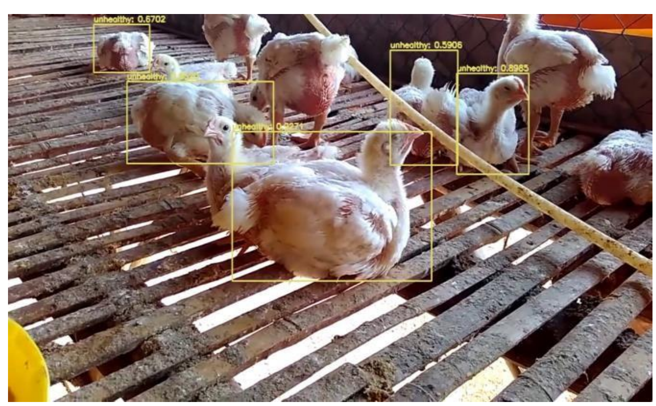


Fig. 11. Output for Healthy Chicken

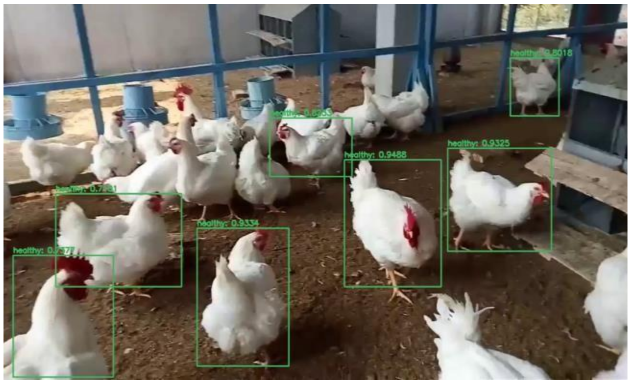
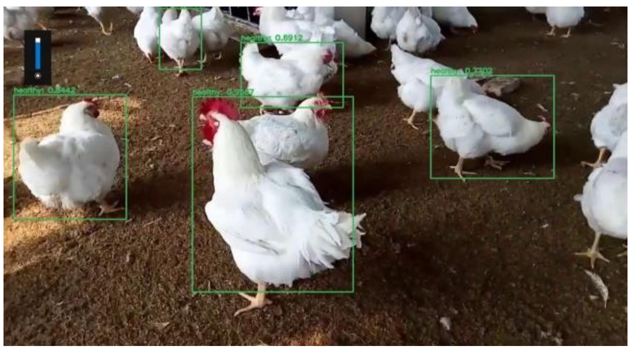


Fig.12. Average Loss of Plotted Chicken



In fig.12, Avg loss of the detected chicken is shown. While training object detection model, there will be average loss which should be less than 0.45 in order to gain good accuracy.In this YOLO Trained model ,the average gains are 0.6912,0.7702,0.8442,0.9667.

MODEL 1 HEALTHY:

Fig.13. Single Frame Taken From Input Video Of Chicken

Fig.14. Command Window Shows the Total Frames and Estimated Time Of Input Video

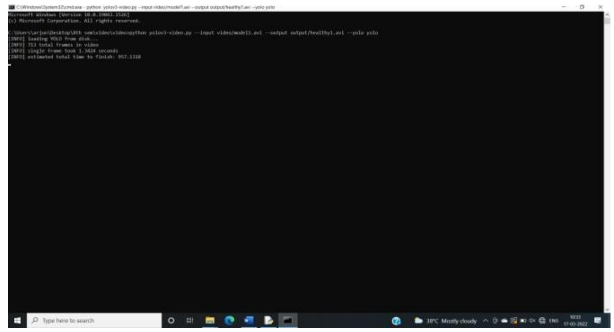
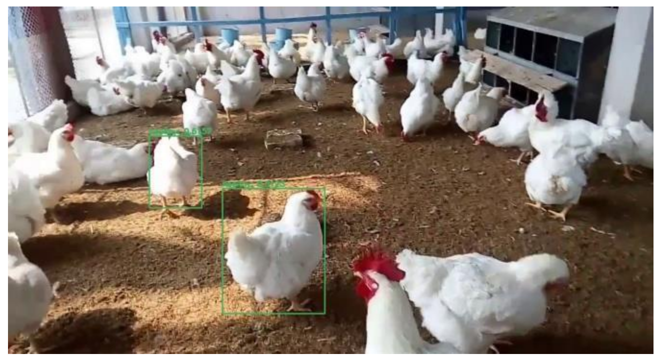


Fig.15. Plotted Output of Healthy Chicken After Testing



MODEL 1 UNHEALTHY:

Fig.16. One Frame Of Testing Video Chicken

Fig.17. Command Window Shows the Total Frames and Estimated Time Of Input Video

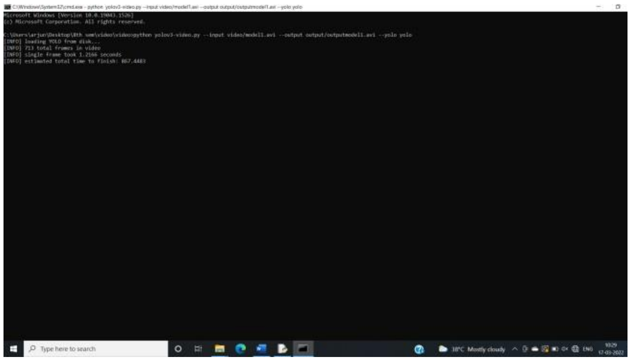


Fig.18. Plotted Output of Unhealthy Chicken After Testing

MODEL 2 HEALTHY:

Fig.19. Single Frame Taken From Input Video Of Chicken

Fig.20. Command Window Shows the Total Frames and Estimated Time Of Input Video

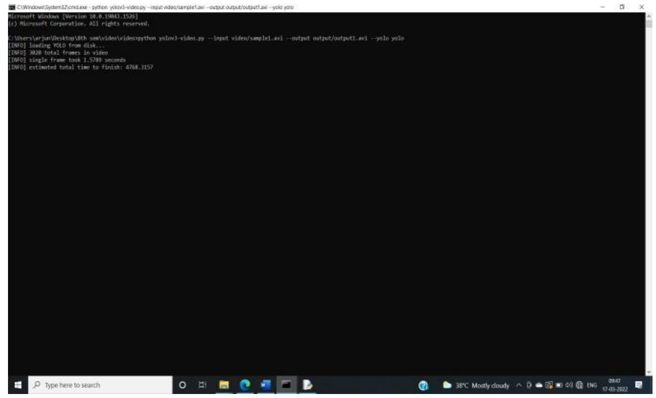
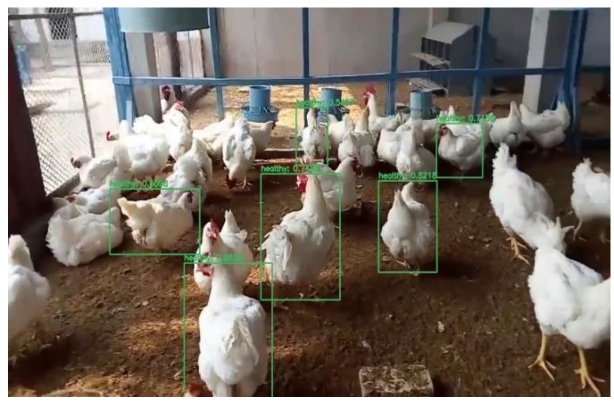


Fig.21. Plotted Output of Healthy Chicken After Testing



MODEL 2 UNHEALTHY:

Fig.22. One Frame Of Testing Video Chicken

Fig.23. Command Window Shows the Total Frames and Estimated Time Of Input Video

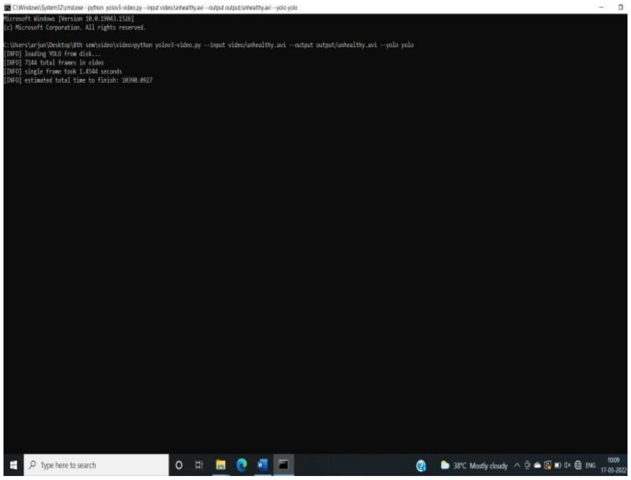
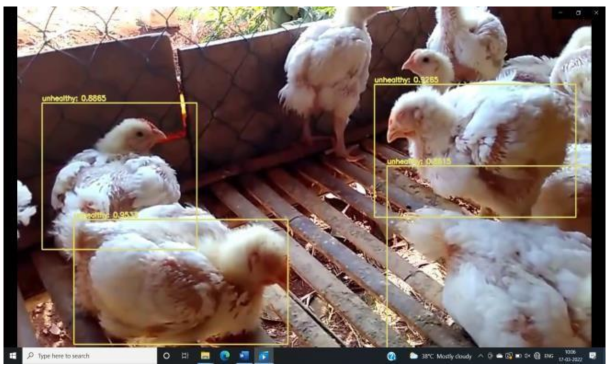


Fig.24. Plotted Output of Unhealthy Chicken After Testing



PARAMETERS OF MODEL 1:

PARAMETERS	VALUES
Batch	32
Subdivision	16
Learning Rate	0.0001
Step size	3800,4200
Width	416
Height	416
Channels	3
Maximum Batches	4000

PARAMETERS OF MODEL 2:

PARAMETERS	VALUES
Batch	64
Subdivision	16
Learning Rate	0.001
Step size	5800,6200
Width	416
Height	416
Channels	3
Maximum batches	6000

The Model 1 and Model 2 are compared inorder to prove which one is more efficient than the other. The main difference among the two models are parameter variation.The parameters like batches,subdivision,step size are varied. In results,there won't be major deviations.Each box prediction is associated with a prediction called Objectness.by considering objectness loss,model 2 is considered as more efficient.

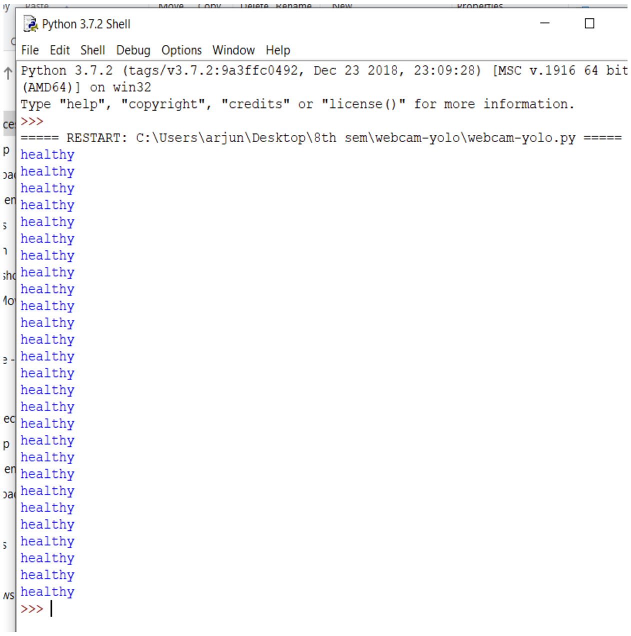
REAL TIME OUTPUT USING WEBCAM

The real-time setup is done and outputs are taken, using Arduino uno and yolo have shown in fig.25 to 32.

Fig.25. Healthy Chicken Detected in Real Time

The above fig.25 shows the chicken detected in the poultry farm(Real Time) using webcam.After evaluating with the training model , it is concluded that the detected chickens are healthy.

Fig.26. Indication of Detected Healthy Chicken in System

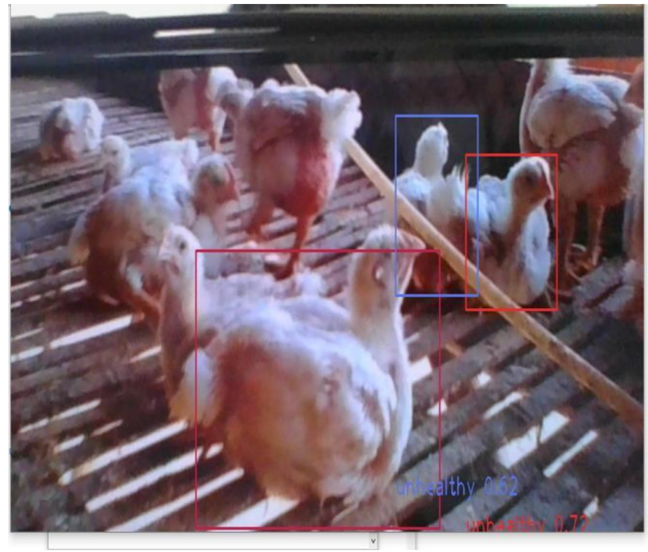


At the same time while detecting the chicken is healthy using webcam, the system that used to operate also displays the chicken is healthy shown in Fig.26.

Fig.27. Display of Healthy Chicken in LCD

After the detection of the healthy chicken in the poultry farm, the LCD display connected to hardware setup displays the chicken is healthy which shown in Fig.27.

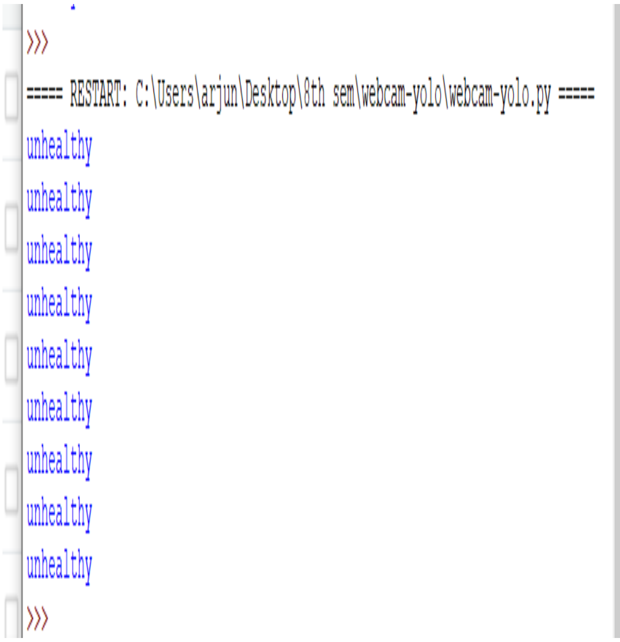
Fig.28. Plotted Output of Unhealthy Chicken in Real Time



The fig.28,29 shows the chicken detected in the poultry farm(Real Time) using webcam.After evaluating with the training model , it is concluded that the detected chickens are unhealthy.

Fig.29. Plotted Output of Mono Unhealthy Chicken

Fig.30. Indication of Detected Unhealthy Chicken in System



At the same time while detecting the chicken is unhealthy using webcam, the system that used to operate also displays the chicken is unhealthy shown in Fig.30.

Fig.31. Display of Unhealthy Chicken in LCD

After the detection of the healthy chicken in the poultry farm, the LCD display connected to hardware setup displays the chicken is healthywhich is shown in Fig.31.

Fig.32. Display of NCD Affected Chicken in LCD

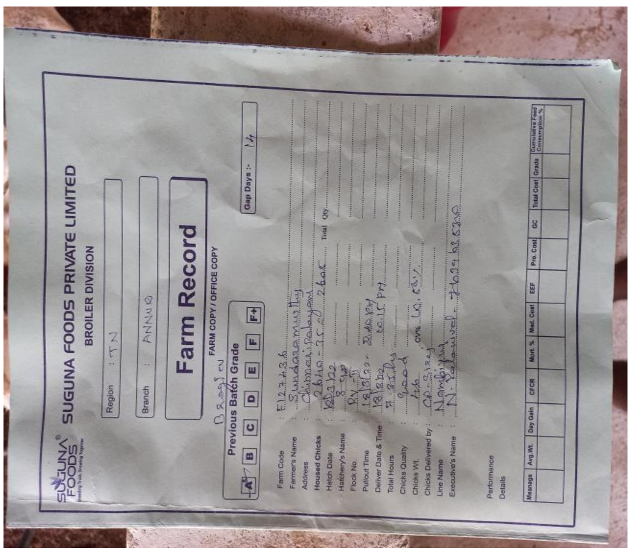
After the detection of the healthy chicken in the poultry farm, the LCD display connected to hardware setup displays the chicken is healthywhich is shown in Fig.32.

VALIDATION BY POULTYRY FARM OWNER

After the completion of the project, validation is done by visiting the poultry farm with both hardware and software setup. Infront of the owner and workers the project is executed and the results are displayed. The results are evaluated by the poultry farm workers whether correct or not. And they concluded that the project is functioning good and it is useful for them. Hereby some images taken in the poultry farm are attached.

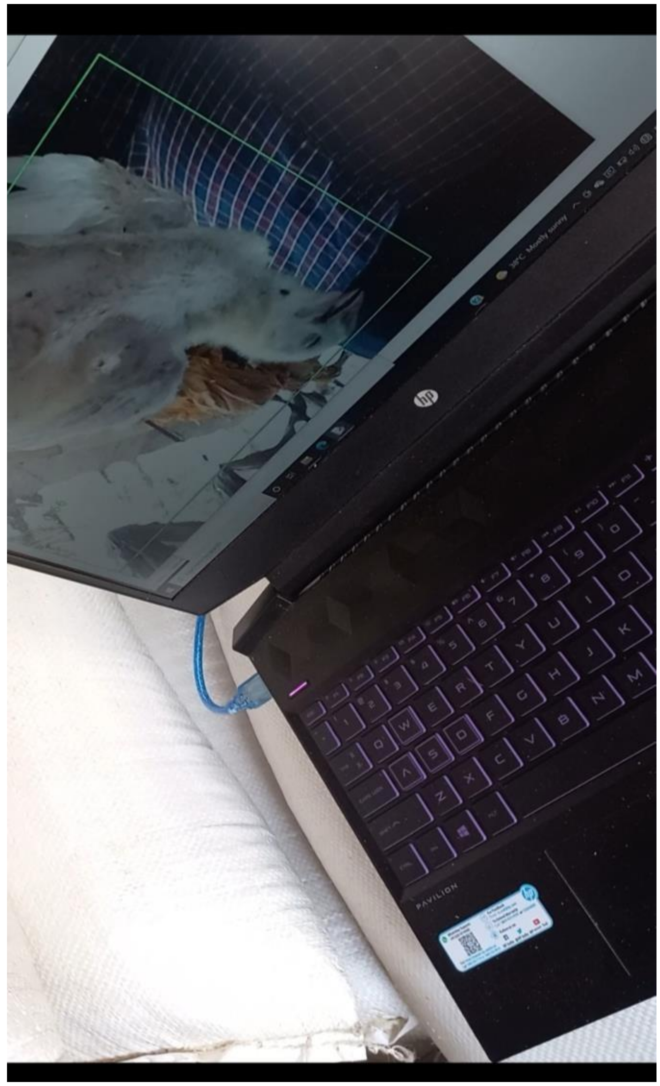
Fig.33. Poultry Farm Entrance

Fig.34. Poultry Farm Record



The above fig.34 consists of poultry farm records like farm owner name, farm code, address, housed chicks, hatch date, hatchery's name, flock no, pullout time, deliver date and time, total hours, chicks quality, chicks weight, chicks delivered by whom, line name, executive's name, performance and day to day activities have been recorded.

Fig.35. Real Time Validation done by Poultry Owner Picking Random chicken



The above fig.35 shows the real time validation, boundary box has been created for random pick by poultry farm owner and our system shows unhealthy then buzzer ringed and also lcd display shows disease detected.

VII. CONCLUSION AND FUTURE SCOPE

As a result of obtaining the centroid for the ill hen, the exact position of the hen in the poultry farm is obtained. The affected hen can be easily separated after the specific location of the sick hen from the poultry farm is identified. The spread of infections can be minimized by separating sick hens in the poultry farm prior to the severity of the condition. It is possible to lower the mortality rate while increasing output.

This study presented a method for detecting broilers and determining whether or not they are impacted by NCD using YOLO version 3. In the application of recognizing numerous broilers in each picture, an object identification model called YOLO was presented. It's a feature-rich SSD with a powerful feature fusion module. In terms of recognizing the health state of broilers, the findings indicated that YOLO v3 obtains mAP of 90.7 percent (IoU

> 0.5) and 48.1 percent (IoU > 0.9). On a single NVIDIA SMI GPU, it operates at 40 frames per second. Finally, the suggested approaches may use photos to identify Farmers may benefit from real-time monitoring of NCD-affected broilers in a flock.

As the demand for poultry grows, poultry farms will be pushed to expand in size and quantity of birds. The need for higher output will encourage producers to be more efficient, and reducing losses will be critical. However, densely crowded poultry farms will likely raise the risk of infection- related losses. Simply said, standard illness and infection monitoring methods will not enough if future production targets are to be met. Instead, quick detection technologies that continuously monitor poultry for disease can be used to supplement existing infectious disease detection and diagnostic systems. Rapid real-time detection can rapidly inform and find producers in the event of a problem. Biosensors will also give manufacturers with a precise diagnostic that is done on-site.

To account for the volume and diversity of data, as well as the necessity for real-time analysis, the dynamic data that will be incorporated in these models will necessitate big data analytics platforms. Multiple hurdles await the application of technology in the poultry production business that improve detection, diagnosis, and prediction of infectious illnesses, yet they will be required to meet future production rates.

This system may be combined with a user interface for end-user remote access. Feeding of chicken hens will be fully automated and incorporated into the system. Environmental characteristics must be monitored in real time in the real estate sector. Using image processing to compare the mobility patterns of ill and healthy chickens to improve prediction and categorization.

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