Utilization of Web Camera and Machine Learning Algorithm in Avian Influenza Symptoms Detection

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Abstract*— Poultry products are threatened by a disease called Avian Influenza or Bird Flu. The study aims to develop a system that can analyze the chickens infected with the disease through symptoms visible to the naked eye. By utilizing a web camera as the eye of the system and implementing machine learning as the brain, the system is developed to detect swelling on a chicken's face. Parameter which is the facial feature will be analyzed by the system and any feedback that is positive will be determined by a bounding box from the Yolo v3 algorithm. The output is displayed through a computer's monitor for the user to easily analyze the results. The Yolo v3 model trained specifically for detecting swollen chicken faces has a result of 69% accuracy in detecting healthy chickens, 56% accuracy of detecting chickens with swollen faces and 70% accuracy of classifying a chicken. The results are from a model trained for 27.6 hours with a dataset of 400 720 pixel images with 900 iterations using Google Colab. The accuracy of detection will increase with a larger dataset and a longer training time as with most Machine Learning Models.

***Keywords*— Avian Influenza, Broiler Chickens, Machine Learning**

I. INTRODUCTION

As the world population continues to increase exponentially as time passes, the demand for food will continue to rise. It is expected that the world population will reach 9.7 billion in 2050 and could peak at nearly 11 billion around 2100 [1]. In order to keep up with this growing number, humans will also need to maintain the production of food like meat, fruits and vegetables. Global meat consumption every year is around 350 million tons [2], which is why poultry industries is vital in maintaining the production of food like chicken meat and other dairy products. This implies that an early detection of potential outbreaks of disease like Avian Influenza will be beneficial to not only to the farm itself but also to the overall productions of food all over the country.

The proposed program would have a major effect on the overall safety management and growth of poultry farms across the country. The program will check data such as facial features from cages where several chickens are handled by assigned staff. The video analysis technique is used to analyze their facial features to help assess whether or not they have signs of the disease. Using the data collected in this process, the program will track and diagnose the presence of the virus in chickens and allow farm managers to remove the infected ones as early as possible.

A solution is developed to detect the presence of av ian influenza in a broiler chicken by training a model a ble to detect swollen chicken faces by using a web cam era and machine learning. Using the Yolo v3 algorithm , this method will exploit developments in modern co mputer vision.Yolo v3 uses CNN or Convolutionary N eural Networks, which is because residual skip connect ions produce and apply 1x1 kernel upsampling on a fe ature map allow detection at three scales.

As Avian Influenza can develop into a highly pathogenic disease meaning it can infect humans and develop a deadly new strain of virus, it is significant to develop solutions that will tackle the problem using the modern technology. The approach of modern researchers mostly focused on contact temperature sensors [4]. The study will focus on a modern solution that utilizes computer vision technology that heavily relies on python programming and data driven model development of algorithms. Avian Influenza will be detected through external symptoms that a chickens face will have when carrying the virus without the need for protein or RNA sequencing [7].

II. RELATED STUDIES

Roy & Sarkar, 2016 developed a real-time device to detect Avian Influenza using low-cost and low-power passive RFID technology for round-the-clock chicken monitoring in a poultry farm [3]. Under the planned scheme, the poultry farm is divided into small cages with paths marked with a stay cage and a food cage. Stay cages are housed for chickens during the day with a passive RFID reader installed at the entrance / exit point to retrieve tag ID information from chicken while food cages act as feed and medication area for chickens where a weighing machine is located at the entrance / exit point of the cage. It is mentioned that chicken weight is one of the key components for monitoring every chicken in that framework.

Zhang, Okada, Kobayashi, & Itoh, 2011 set up a high-performance avian influenza monitoring system focused solely on the monitoring of body temperature and activity using a prototype wireless sensor node [4]. According to experimental and simulation findings done, influenza infection, including highly pathogenic avian influenza (HPAI), may be detected by a wireless sensor node 10 hours prior to death. This was also found that early-stage diagnostics and alarms could be done by tracking the safety of 5 percent of the chickens. Unfortunately, the battery life of the wireless sensor node does not comply with the practical prerequisite, which must be 2 years.

Chinese researchers at the University of Shenyang Agriculture and the University of Arkansas have developed a microelectrode impedance biosensor for fast, accurate and sensitive detection of multiple avian influenza viruses [5]. In this study, virtual instrumentation using a laptop equipped with LabVIEW was used to produce excitation signals at different frequencies with an audio card and to measure the impedance of target viruses with a data acquisition card. The developed portable biosensor, which combines an interdigital microelectrode based array check with a virtual instrumentation based impedance measurement tool, is suitable for real-time field usage.

According to the published research by K. Nishihara et al. birds infected with avian influenza experience swelling and inflammation in their feet, and it is thought that these symptoms may be reflected in the flow of blood [6]. In line with this, an integrated Doppler blood flow micrometer for chickens has been devised. In order to measure chicken blood flow for five consecutive days, researchers have developed a microelectromechanical system (MEMS) sensor using a laser doppler flow meter (LDF) as a non-invasive blood flow meter. The machine is portable, weighs just 18 g and has low power consumption. Both features made it possible for the sensor to be attached on chickens and to monitor their blood flow under normal conditions. The sensor system is designed to capture only a small number of values over a relatively short timeframe to mitigate interruptions due to spike noise and to provide reliable and precise blood flow records.

The computational, artificial neural network (ANN) learning-based approach to the proposed method used by Chrysostomou, Partaourides, and Seker, 2017, is designed to evaluate if a particular virus is capable of infecting humans by only analyzing the Haemagglutinin protein sequence [7]. Out of the Influenza Research Database, 30724, 18236 and 8157 HA protein sequences have been collected for human, avian and swine. A 10-fold cross-validation was used to ensure that the proposed classification model was correct and that the results could be generalized. According to this paper, a computational model capable of classifying and recognizing potentially harmful viruses capable of infecting human hosts will be appropriate and adequate for the monitoring of possible outbreaks. Future work will explore additional machine learning techniques to investigate the performance of the framework, using signal processing methods to decode protein sequences.

The group of H. Okada et al. have created a wearable wireless node sensor for the avian influenza surveillance network in a chicken house [8]. The body temperature and movements of the chickens can be tracked by attaching a wireless sensor node with a temperature sensor and an accelerometer to the chicken. Unfortunately, as there are a very large number of chickens in the chicken house, only the minimum density of wireless sensors can be controlled. When the monitoring program senses the abnormal condition of the chickens, the software automatically alerts the administrators via the internet. With these tests, the occurrence may be determined whether or not it is caused by avian influenza. The machine can also record a history of health problems obtained by sensors such as fever and fatigue. It was found that if the sensor nodes were equipped to around 5 percent of the chickens, avian influenza could be identified by the sensor network 2 days earlier relative to the current patrol.

III. METHODOLOGY

For Avian Influenza Symptoms detection, both the camera and the machine learning algorithm to be used must to be chosen carefully. The best camera that is suitable for this project should be capable of capturing images at a resolution that is not very high which could lead to huge processing loads nor very low that could affect detection accuracy. For the most part, the camera to be used should be dependent on the computational capability of the hardware. For this project, a web camera of 720p resolution was used.

In choosing the suitable machine learning algorithm to be used for object detection, two very important variables were considered. The first one to be considered is the algorithms processing speed with limited hardware capability. This factor is very important for this project since for a portable device which has a limited power source, it should be expected that there is also a limited hardware processing capability available, at least for the time this project was developed. It is worth noting that most machine learning algorithm that uses neural networks requires considerable processing power. The second factor worth considering in the selection process is the accuracy of the algorithm in terms of object detection in images. Different machine learning algorithms have different accuracy levels which sometimes depends on where it will be implemented or used. For this project, YOLO v3 algorithm was used since it has both the processing speed and detection accuracy required.

A. Gathering of data

Before YOLO v3 algorithm can be used, it is essential that sufficient data will be gathered for the training and development of the machine learning model. The gathered data involves images of both healthy and unhealthy chickens taken using the same camera to be used by the device. Having the same camera used for both data gathering and project implementation helps in terms of the overall detection accuracy of the device.

B. Training Preparations

A data set consisting of training data and test data is required to create a customized weight for image processing. The data was further divided into positive and negative pictures. Most of the images obtained were taken using the same camera that will be used by the program. This is to ensure that the resolution of the images used for its training is the same as the resolution of the images that the system will get through its camera. Using different image resolutions during the training and implementation of the device would result in a substantial decrease in the accuracy of both its object detection and position.

The collected images were labeled using LabelImg program, a program that is used to prepare images for training by generating a text that sets the pre-determined position of the object we want to identify and its label name, which in this case refers to the face of infected broiler chickens.

Figure 1. Using LabelImg for Data Preparations

This figure shows the editing area, the LabelImg interface and the data acquired for the object detection model training that are prepared for labeling and then converted to an npy file or a NumPy file and will serve as an anchor for images during model training

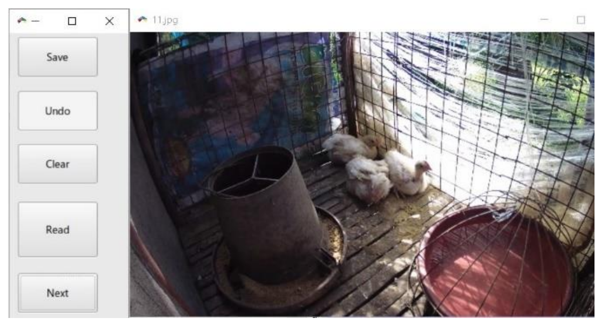

Figure 2. Using LabelImg for Data Preparations

This figure shows the editing area, the interface of LabelImg, and data acquired for feature analysis model training by the proponents being prepared for labeling and then be converted to npy file or NumPy file and will serve as an anchor for images during the training of the feature analyzing model.

C. Setting up the Training Environment in Google Colab

Google Colab is used by most programmers training models because it allows anybody with a google mail account to use Google's GPU or TPU to train massive amounts of data limited to 12 hours a day for free. This is a feature that should be utilized by programmers of machine learning and deep learning algorithms. But Google Colab does not come with a template of codes. To be able to train using Google Colab, a user must set it up according to his/her requirements. Training with images as datasets will become easier if these datasets are uploaded to Google Drive. The process of training gets a boost if the dataset is zipped and then unzipped directly to colab but the advantage of doing so is that once you restart the kernel or the terminal, the uploads made will be deleted so this process is volatile.

```
from google.colab import drive
drive.mount('/content/gdrive')

Go to this URL in a browser: https://accounts.google.com/o/oauth2/auth?client_id=947318

Enter your authorization code:
..........
Mounted at /content/gdrive

[ ] %cd gdrive/My Drive
    !git clone https://github.com/pjreddie/darknet
    !ls
```

Figure 3. Pre-Training on Google Colab

This figure shows some of the pre-training processes that the proponents used to setup the training for the Yolo v3 Model of the AID-System. The first box contains code that initializes the google drive that will be accessed by the current python notebook. The second box clones darknet from the URL which contains the presets such as the epoch and learning rate of the training process.

D. Training for YOLO v3 Algorithm

During training, it is recommended that a powerful computer with high end GPU is used to improve both training speed and the accuracy of the model. Another option is to use cloud computing for training which are available on the internet. The machine learning model for this project was trained with the help of Google Colab, a free online cloud computing platform by Google.

The training of the YOLO v3 model for image processing was done through Google Colab, an online cloud service by google in which they are letting people to have access in their available GPUs and use it for free. This accelerates the training process overall and also made it possible to set higher epoch values for the training which also improves the accuracy of the model. This is not achievable with normal computers since the higher the epoch value, the better the GPU that it requires. A pre-trained weight was also used to improve the accuracy of the final weight to be used for image processing. Another requirement for the training is that Darknet must be installed in the system together with the pre-trained weights of YOLO v3 for faster and more reliable results.

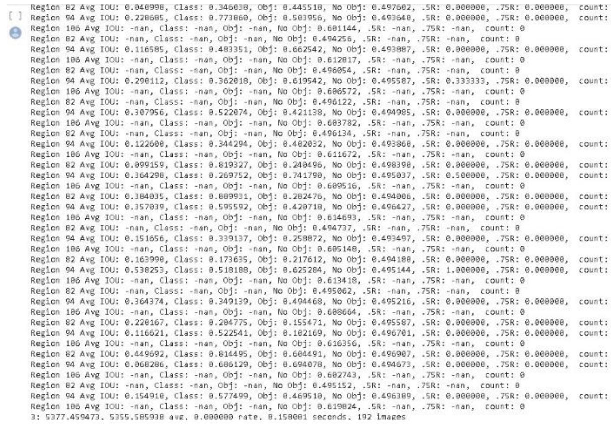

Figure 4. Training of the model in Google Colab

The figure shows the training process of the model weights of the Yolo v3 algorithm in google colab with the help of the modified darknet specifically to fit the needs of the training of the data acquired from the farm setup and the setup built by the proponents. Unlike training a model with only numbers as datasets, training models with pictures of high resolution takes much more time as observed by the proponents.

E. Yolo v3 Object Detection Testing Phase

The testing phase was done several times with a dataset containing different resolutions of photos of chickens to determine how it affects the accuracy of the Yolo v3 object detection model weights. This is intended to also identify how lighting can affect the detection of the subject which is the chicken.

Figure 5. YOLO v3 Object Detection Testing

This figure shows the YOLO v3 object detection model weights testing on an actual photo of the chicken which uses the image processing technology to detect the intended subject. As seen from the figure, the chicken was detected and the program was 97 percent sure that the object is a chicken.

F. Yolo v3 Feature Analysis Testing Phase

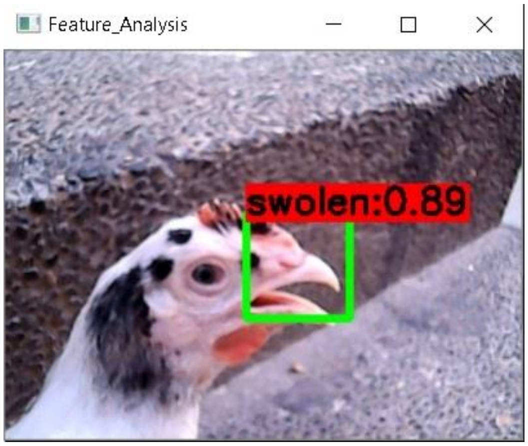

Figure 6. YOLO v3 Feature Analysis Testing

This figure shows the YOLO v3 algorithm feature analyzing the model weights tested on the actual chicken picture, which uses the image processing technology to analyze the face of the subject. As shown in the figure, the face of the chicken was assessed to be swollen, despite the black marks on its face that are not commonly seen on the face of the chickens. As seen in the figure, the YOLO v3 algorithm analysis was 89% positive that the chicken's face was swollen.

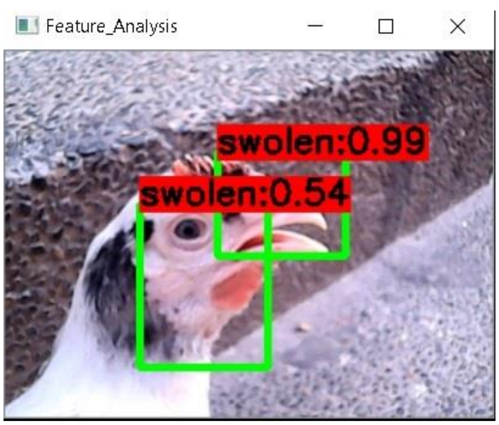

Figure 7. YOLO v3 Feature Analysis Testing

This figure shows the Yolo v3 algorithm while using the trained model in analyzing an image of an actual chicken. As seen in the figure, the face of the chicken was assessed to be swollen, depicted by a bounding box which encloses it. Above the bounding box is the percentage value of how sure the algorithm about its prediction, which in this case is 99%.

G. Yolo v3 Object Detection Flow Chart

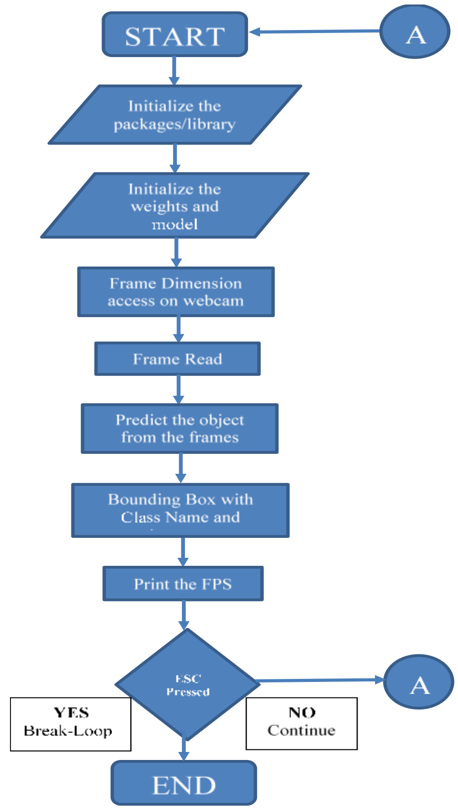

Figure 8. YOLO V3 Flow Chart

Real-time video data is taken from our 720p resolution web camera, which is chosen for this reason because of its mid-range resolution and will be useful specifically for the detection of the object, which is the chicken in our case. When taking videos in real-time, video data is transmitted simultaneously to the computer, allowing the video processing program to have the data it needs. After data acquisition, the program begins the process of pattern recognition through machine learning. The recognition of symptoms displayed by the chickens is then performed through You Only Look Once v3, an algorithm widely used for classifying items using convolution neural networks.

You Only Look Once v3 or YOLO v3 is a type of Machine Learning Algorithm that uses neural networks to speed up the process of object detection. For this type of algorithm, the computer is trained by allowing it to train the model of the given input to the appropriate output, since the output for the given input is known beforehand (GN, n.d.). The processing of the video must include the processing of the image as a subpart of it. YOLO v3 uses a bounding box that encloses the object identified on the basis of its qualified model and demonstrates how assured the algorithm is in classifying the object bound by the box. This is why camera resolution is crucial to video processing.

IV. RESULTS AND DISCUSSION

Using YOLO v3 algorithm for object detection in broiler chickens to detect symptoms for avian influenza based solely on their facial features has shown some interesting results. During initial testing, the system was able to correctly determine and distinguished broiler chickens with influenza symptoms from healthy broiler chickens accurately under normal lighting conditions as shown in the figure below.

The results have also shown that lighting conditions affects the algorithm's effectiveness and accuracy for object detection.

The results also shows that using the system in detecting avian influenza symptoms for two or more broiler chickens drastically decreases the processing speed of the system for image processing. It also affects the localization process, which directly determines the accuracy of the system's detection capability. It would mistakenly set up wrong bounding boxes, which means that the system is having problems in predicting the correct localization points. Even though YOLO v3 algorithm is considered to be among the best machine learning algorithm available in terms of its object detection capabilities, it would still require a more powerful hardware than what is used in this system to perform well for multiple object detection.

Another factor that directly affects the accuracy of YOLO v3 algorithm in terms of object detection is the distance of the chicken from the camera. As the distance increases, the accuracy drops significantly as less information is being fed into the system. It is therefore recommended to have the broiler chickens be close enough to the device when using it.

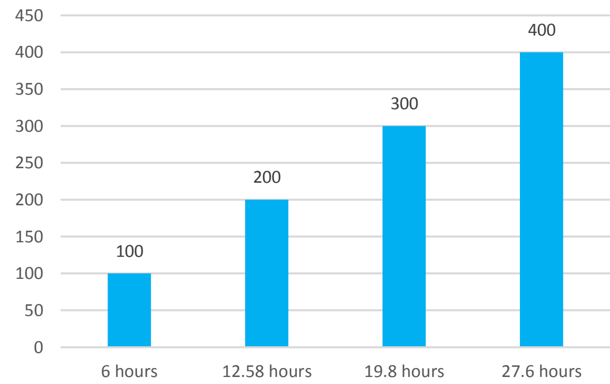

FIGURE 9. NO. OF IMAGES VS. TRAINING TIME

The figure shows the number of hours it took to train a model with a dataset containing 100, 200, 300, and 400 720pixel images to 900 iterations with the default darknet. It can be observed that the training time is significantly larger when the images used as data increases.

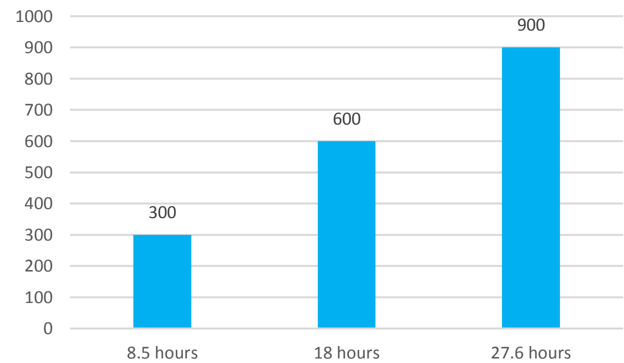

FIGURE 10. NO. OF ITERATIONS VS. TRAINING TIME FOR 400 720P IMAGES

This figure shows the number of hours it took to reach checkpoints at 300, 600 and 900 iterations for a dataset containing 400 720pixel images. It can be observed that the number of hours is directly proportional to the number of iterations.

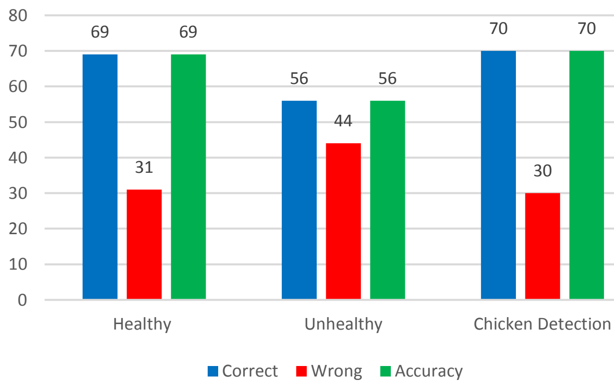

FIGURE 11. YOLO V3 ALGORITHM OBJECT DETECTION ACCURACY

The figure demonstrates the precision of the YOLO v3 algorithm for the identification of features trained by the proponents. The diagram indicates the number of correct detections, the number of errors and the accuracy of the results by the number of correct detections divided by the total samples. The model used was trained using 400 720pixel images which reached an anchor of 900 iterations for weights.

V. CONCLUSION

YOLO v3 was used as the algorithm for Object Detection. The accuracy of the detection of swelling in the face of the chickens depend on the number of data used in training and the time spent in training the YOLO v3 Machine Leaning Model. The resolution of the images used as dataset affects the time required to train a reliable model.

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