UNIVERSITY OF NAIROBI
FACULTY OF SCIENCE AND TECHNOLOGY
MSc. Computational intelligence

A COMPUTER VISION SYSTEM FOR EARLY DETECTION OF SICK BIRDS IN A POULTRY FARM USING CONVOLUTION NEURAL NETWORK ON SHAPE AND EDGE INFORMATION.

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A research proposal submitted to the School of Computing and Informatics in partial fulfillment of the requirement for the award of Master of Science in Computational Intelligence at the University of Nairobi.

Declaration

I declare that this work is my original effort and has not been previously submitted for academic credit or any other purpose. I have taken all necessary precautions to ensure that the work is entirely my own and does not contain any unauthorized or unacknowledged material. I understand that any breach of academic integrity may result in severe penalties, including but not limited to a failing grade or expulsion from the program. Therefore, I affirm that the work presented in this document is entirely my own, except where duly acknowledged in the text.

Signature.......................................

Date........23/03/2023...............

Name: Joel Amenya Orandi

Supervisor

This project has been submitted in partial fulfillment of the requirements for the Master of Science in Computational Intelligence of the University of Nairobi with my approval as the supervisor.

Signature.....................................

Date......23-03-2023.......................................

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Abbreviations and Acronyms

YOLO	You Only Look Once
SSD	Single Shot Multibox Detector
R-FCN	Region-based Fully Convolutional Network
R-CNN	Region-Based Convolutional Neural Networks
3D	Three Dimensions
2D	Two Dimensions
ResNet	Residual Network
ResNext	Next-generation Residual Networks
DenseNet	Densely Connected Convolutional Networks
GDP	Gross Domestic Product
WMFCC	wavelet transform Mel frequency cepstrum coefficients
CDF	Correlation Distance Fisher Criterion
HMM	Hidden Markov Model
SDG	Sustainable Development Goal
UAV	Unmanned Aerial Vehicle

ABSTRACT

Poultry farming is increasingly becoming popular because it provides cheap alternatives to animal-based proteins in the form of eggs and meat. It is also easy to practice poultry farming because it does not require very large pieces of land to do poultry farming. However, large-scale poultry farming faces the challenge of disease management. Most of the time, routine vaccination, and healthy feeding have been relied on to promote healthy growth and production of poultry products. However, these practices are not sufficient to fully address the problem of disease management in poultry farming. One of the most assured ways of managing disease is close monitoring and detecting sick hens early enough before the disease spreads catastrophically. This study aimed at developing a computer vision system for the early detection of sick birds in a poultry farm using a convolution neural network on shape and edge information. This was achieved by creating a labeled dataset of sick and healthy birds based on edges, ridges, and Harris corners. Four convolution neural network models were trained, one based on full feature sets of the images while the other three were based on edges, ridges, and Harris corners. The purpose of training the different models was to establish which descriptors can best predict the health status of a hen based on its appearance of the hens. The assumption was that sick hens generally have their wings and tails stoop downwards with a weak neck that is bent downwards. Images were captured using a camera and used in four convolution neural network models. Three models were based on the features extracted (Ridges, edges, and Harris corners) while the other model was trained based on the full image without removing a single feature. The models were compared in terms of their accuracy of prediction.

The models were evaluated based on performance during training and performance on unseen data. The model based on Harris corners was found to perform best at an accuracy of 94.14% while the model based on full feature sets was found to perform least with an accuracy of 46.66%. The model based on Harris corners was used to develop a web-based system that was deployed to predict the health status of hens in a poultry farm. The study was able to achieve its objective and proved that it is possible to classify healthy and sick birds based on a single feature.

CHAPTER ONE: INTRODUCTION

1.1 Introduction

The benefits of having a balanced diet are enormous. They include the ability of the body to fight and prevent diseases and infections. Proteins are key components in achieving a balanced diet. Proteins can be plant-based or animal based. Producing plant-based proteins that can sustain the world population usually requires huge tracks of land, a lot of water, and labor. This has made plant-based proteins not to be enough hence the need to supplement plant-based proteins with animal proteins. One of the choices for animal-based protein is chicken meat and eggs. This is because chickens take a short time to mature, and they require a small amount of space and little labor to rear. Until very recently, poultry production has been confined to small-scale and backyard production. (Vetrivel et al, 2013).

It is expected that the world population will be 9.2 billion in 2050 (Tilman et al,2011). As this population increases so does the demand for chicken-based proteins. This has necessitated the rearing of poultry on large scale. But this has brought about certain challenges that largely only affect large-scale poultry farming. Some of these challenges include low productivity, poor feeding, diseases, poor management, and lack of an organized market. Of these challenges, diseases are considered the main problem since it causes massive losses when the birds die, or they can cause human infections if not properly handled. To be effective in poultry farming, the methods used to manage diseases in poultry farms must be improved. Traditional methods have been applied over the past many years. They include giving vaccines on a routine basis and monitoring the birds as they grow. But even with these management methods, sometimes sick birds go unnoticed in large farms. At the same time, observation usually suffers from human errors and varied judgment capabilities in different people.

Computer technologies, especially in the area of artificial intelligence, have been used in a variety of application areas to solve problems that require high intelligence to the level of human intelligence. Of interest is computer vision which is a form of artificial intelligence that enables systems to derive meaningful information from digital images. This research is about developing a computer vision system that will use cameras to observe birds in a poultry farm and detect sick ones and alert the farmer so that they take necessary actions.

1.2 Background to the study

Poultry farming constitutes 55% of the livestock sector and 30% of the agricultural gross domestic product (GDP) in Kenya. This is 7.8% of the total national GDP (Justus et al, 2013) The demand for protein has continued to be on the rise as the population increases. Farmers are beginning to go large-scale in eggs and poultry meat production. (Atuahene et al, 2012) explored the prospects and challenges of poultry farming in Ghana. They found out that disease was among the challenges that must be dealt with to make poultry production profitable. (Munyaka, 2010) did a similar study in Kenya, even though their findings were that marketing is the major challenge in poultry farming in Kenya, diseases still featured as a challenge. 50% to 100% of susceptible chickens particularly chicks are killed by disease (Ahlers et al., 2009; Sonaiya & Swan,2004).

Various methods are being used to address disease control in poultry farming. Some of these methods are manual and depend on human intervention while others are computer-based. The manual methods are not scalable and may not apply to large-scale farms as monitoring and observing each bird on a large-scale firm will be a near-impossible mission. By the time the farmers realize it, it is too late, and the disease may have catastrophically spread.

Computer-based systems that use computer vision technologies have also been used to monitor birds and detect sick ones automatically. For example, (Nasirahmadi et al,2020) developed a system that uses audio analysis to detect chicken suffering from a respiratory infection and (Wang et al,2019) developed a system that analyses poultry droppings to detect chicken suffering from a digestive infection. These solutions implemented convolution neural networks in doing image classifications. However, they have not effectively addressed the challenge hence the need for further academic research into the area. Most poultry diseases manifest themselves through lack of appetite, appearing weak and sleepy with drooping necks, tails, and wings. These symptoms can be used in a computer vision task to identify sick and healthy birds

Convolution neural networks are powerful computer vision algorithms for performing image classification and they provide an opportunity to identify sick birds by looking at the features in an image that can discriminate between the images

1.3 Problem statement

Disease management in poultry farming remains the biggest challenge that farmers must deal with to make poultry farming profitable and poultry products safe for human consumption. Most farmers try to give vaccines to their flock on a scheduled routine and observe both sounds produced by the birds and their visual appearance and activity level. These methods are not very effective as they cannot be applied to large-scale farming. Due to these limitations, when disease strikes and is not detected at early stages, it ends up spreading catastrophically.

Several solutions have been fronted to try and address the problem. For example (Nasirahmadi et al,2020) developed a system that uses audio analysis to detect chickens suffering from respiratory infections. (Wang et al,2019) developed a system that analyses poultry droppings to detect chicken suffering from a digestive infection. However, even with these solutions, poultry disease continues to be a threat to poultry production. The solutions proposed are highly specialized. For example, the solution to detect respiratory infection cannot detect digestive infection and vice versa. This makes it expensive to install multiple systems to holistically observe the birds, yet most of these diseases can also manifest themselves in the general look of the birds. The existing solutions also have a challenge in that they may not work in real-life situation because it becomes difficult to identify the bird that produced a suspicious sound in the case of analyzing sound to detect respiratory infection. It is equally difficult to match the droppings to the birds that produced them in the case of analyzing broiler droppings to identify respiratory disease. In both the works of Nasirahmadi et al and Wang et al, labeled images were used to train a convolution neural network. The network assigned weights to learnable features from the images. While it is true that some features are better descriptors than others in any image processing task, Nasirahmadi et al and Wang et al did not show which features perform better than others. This is also true with other scholars in the field of computer vision, for example, Aydin A, 2017, Kristensen et al, 2011 and Pereira et al,2013.

1.4 Research questions

i. Do some features perform better than others in image classification tasks?

ii. To what extent do edges, ridges, and Harris corners as image features correspond to the health status of poultry birds?

iii. How possible is it to train a convolution neural network to classify birds' images as sick or not sick based on a single image feature?

1.5 Objectives

1.5.1 Overall Objective

To develop a computer vision system for the early detection of sick birds in a poultry farm using a Convolution neural network ~~on posture information~~

1.5.2 Specific objectives

i. To create a labeled dataset of sick and healthy birds based on edges, ridges, and Harris corners.

ii. To train a convolution neural network to classify poultry images as sick or not sick based on edges, ridges, and Harris corners and determine the best-performing feature.

iii. To develop a system for detecting sick birds in a poultry house based on the best-performing feature.

1.6 Significance

This project aligns with SDG Goal 1: No poverty under the target of eradicating extreme poverty for all people everywhere, currently measured as people living on less than $1.25 a day. By closely monitoring chickens on the farm, sick birds will be quickly identified before spreading the disease to the rest of the birds. This will reduce losses and minimize disease transmission to humans in case there is an outbreak that spread without being noticed. This way, more money is available to earn people a living above $1.25, money that would have otherwise been used to treat the birds and humans as a result of disease transmission. The project is equally aligned with SDG goal 12: Responsible consumption and production under the target of halving per capita global food waste at the retail and consumer levels and reducing food losses along production and supply chains, including post-harvest losses by 2030. It also aligned with agenda 3 of the big four agendas as conceptualized by H.E President Uhuru Kenyatta in 2017 which talks about food security to ensure all Kenyans are well-fed, looking at poultry farming as a source of food, the well-being of the sector fully relies on the good health of the birds.

1.7 Justification

This project aims at developing a computer vision system for the early detection of sick birds in a poultry farm using a convolution neural network on shape and edge information. This is in response to the need of managing poultry diseases to reduce the risk of death of the birds that can result in huge losses as well as the need to lower the risk of human disease as a result of interaction with sick birds. There are existing computer vision solutions that are highly specialized and monitor only specific parts of the birds. This makes it expensive to install multiple systems to monitor different aspects of the birds to provide holistic monitoring of the birds. There is a need to have one solution that will monitor the birds holistically and report the birds that appear sick from physical observation. There is also a need to evaluate whether the convolution neural networks will perform better if they are guided to use edge and posture information in classifying the birds as healthy or not as opposed to letting the models learn the features to use during training.

1.8 Limitations and assumption

While the algorithm will be able to classify the birds into sick or healthy classes, it will not be able to diagnose or predict the actual disease the birds are suffering from.

CHAPTER TWO: LITERATURE REVIEW

2.1 Introduction

The world population is expected to be 9.2 billion in 2050 (Tilman et al,2011). With this huge population, food security will continue to be a challenge unless a deliberate effort is taken to address the problems. One of the sources of protein is poultry products, which makes it necessary to control disease in poultry for maximum yield. Among the things that can be done is monitoring poultry for early disease detection and treatment before the disease catastrophically spreads. A lot of research has been done to try and address the problem of early detection of sick birds in a poultry farm before the disease catastrophically spreads. Some of the methods used are not computer-aided, for example, Vaccination, boosting the immune system of birds, minimizing stress on birds, and Quarantine measures among other methods (Sharif et al, 2014) while others employ the use of computers to make monitoring more precise. More especially in the recent past, advancements have been made in artificial intelligence to accurately perform monitoring for early disease detection not only in poultry but in animals at large.

2.2 Computer vision

Computer vision involves giving computer systems the ability to gain a high-level understanding of visual information from images and videos. Given this capability, computer systems have been able to perform visual tasks in an array of application areas ranging from the medical field, industrial application, and agricultural field to the automobile industry. The application of computer vision is not a new discipline. According to (Smulders et al, 2006), the main reason for automatic monitoring of animals is to monitor animal welfare to detect as early as possible any event that compromises animal welfare. Some examples of vision systems for animal monitoring include systems such as animal weight estimation by (Banhazi et al,2009), machine vision systems for detecting the behavior of cattle and pigs (Nasirahmadi et al, 2017), and 3D Vision for Precision Dairy Farming (O'Mahony et al,2019). In poultry farming systems such as the use of deep learning and acoustic data to detect pecking activities in turkeys (Nasirahmadi et al,2020), 3D vision cameras system to automatically assess the level of inactivity in broiler chickens (Aydin A, 2017), and broiler dropping analysis for digestive disease detection by (Wang et al,2019) have been developed. While there have been computer vision systems for monitoring animal and chicken welfare, most of them only work well in controlled environments and cannot be practically deployed in monitoring the animals in their natural environment.

2.4 Image Features

Image features are pieces of information about the content of the image. Image features are useful in fulfilling various image processing tasks like image tracking, image classification, and object detection among other tasks. Knowing the techniques for extracting image features is useful in achieving any computer vision task. Image features can be classified into two broad categories, i.e General features and Domain-specific features (Choras et al 2007). Chore et-al review Color, texture, and shape and the steps involved in extracting them. The choice of features to use in image processing highly depends on the nature of the task involved.

2.4.1 Edges

Edges are points of discontinuities in an image. These points of discontinuities can be a result of a sudden change in color, contrast, or brightness. Various algorithms exist for performing edge detection. For example, Sobel Operator, Robert's cross operator, Prewitt's operator, Laplacian of Gaussian, and Canny Edge Detection Algorithm. Canny edge detection is an optimum edge detector. (Maini et al, 2009). It uses probability to reduce error rates. It improves the signal-to-noise ratio making it perform better in noise conditions.

2.4.2 Harris Corners

Harris corner detector is a corner detection operator that has found a lot of applications in recent computer vision tasks. It can be used to retrieve similar images using interest points (Velmurugan et al, 2011). Though other corner detection operators exist, the Harris corner detector remains the most used operator because it is fast, robust, and rotation invariant.

2.4.3 Ridges

Ridges are a common feature of interest in image processing. They are preferred because of their invariance to most transformations eg rotational transformations. Several algorithms for ridge detection have been proposed. For example, Edge detection and ridge detection with automatic scale selection (Lindeberg, T,1998)

2.5 Early detection of sick poultry birds

Early detection of sick poultry birds has been very key in managing disease in farms. Several studies have proposed methods for early disease detection in chickens and broilers. (Zhuang et al,2018) developed an algorithm to detect sick broilers. In their result, they found out that support vector machines (SVM) obtained higher accuracy in the early detection of disease. One of the features that they used in early disease detection was the shape of the birds. This confirms that shape is an important feature in disease detection. However, they did not attempt to use this feature with a convolution neural network.

2.6 Convolution neural network

A convolution neural network is a deep learning algorithm mostly used for image classification. It takes a grayscale image as the input and assigns learnable weights to the features in the image. It then uses these features to classify images.

2.7 Existing work

Different scholars have attempted to explore various aspects of not only poultry health but animal health in general. This ranges from automatic animal temperature detection which could be used to infer the health status of the animals or birds, behavior analysis and classification, image analysis of animal wastes, monitoring of animal activities and frequency of movement to the audio analysis of the animals or birds to determine the existence of respiratory infections. This section reviews some of these existing works

2.7.1 Audio analysis to classify birds as sick or healthy

Audio processing can be used to classify the health status of birds and animals in general. This is possible because birds and animals produce different sounds when infected with respiratory disease. (Nasirahmadi et al,2020) used deep learning and acoustic data to detect pecking activities in turkeys. Though this might not be practically used in disease diagnosis, pecking activities can be used to infer underlying health issues because healthy birds will peck in a way that is different from sick birds. Deep learning on animal sounds can potentially be used to distinguish between sick birds and animals from healthy ones.

2.7.2 Walking speed and frequency of movement to classify birds as sick or healthy

Walking speed and frequency of movement can be used to detect diseases or lameness of animals. (Aydin A, 2017) developed a 3D vision camera system to automatically assess the level of inactivity in broiler chickens. He used different gait scores, one obtained by human experts and the other by the image processing system. He then analyzed the different gait scores to identify the broiler behavior. When the level of inactivity is lower than expected, it implies that the broiler has a health-related problem and the farmer is alerted for timely action. A similar study was done by (Kristensen et al, 2011). In their approach, they described the undisturbed levels of activity of chickens over three weeks. They accomplished this in three steps. First, they applied a model, which was able to filter out outliers in the data stream of automatically recorded activity from overhead video cameras. Secondly, they described the undisturbed levels of activity in groups of broiler chickens for a day in weeks 1, 2, and 3, and lastly, they applied a method to detect deviations in activity level, thereby indicating a level change in activity within the flock of broilers. Deviation of activity from the expected level at a given age could imply an underlying problem like disease, lameness, or just something wrong with the general welfare of the broilers. Another research in the same domain was presented by (Pereira et al,2013). In their research, they use image processing technology to recognize the behaviors of white broiler breeders. They applied combined techniques of image processing and computer vision to different body shapes from a sequence of frames as the birds expressed their behaviors. Their method was a four-stage method. First, they identified body positions and their relationship with typical behaviors. Secondly, they collected image samples, with the isolation of the birds that expressed behavior of interest. Thirdly, they did image processing and analysis using a filter developed to separate white birds from the dark background; and finally, (4) construction and validation of a behavioral classification tree, using the software tool Weka (model J48).

2.7.3 Growth rate observation to infer poultry health

(Kashiha et al,2013) describe Anomalous bird behavior and reduced growth rate as some of the common signs that can indicate an undesired situation in a broiler house. While anomalous bird behavior or reduced growth rate might not necessarily imply a disease breakout in the farm, they provide a good heuristic for the possibility of a disease outbreak. (Kashiha et al,2013) proposed an automated way of detecting problems in a poultry house using cameras and image analysis software. Problems could be anything ranging from broken feeding equipment, poor lighting, and unventilated room to diseases, leaking rooms, etc. Given the broad range of what can fit into the definition of a problem, this kind of automation becomes a complex task because of the extreme dynamics brought about by different problems. Obtaining a single solution that fits all these problems is not a trivial task. Nonetheless, their paper provides a good starting point. A sick bird can be considered a problem whose identification can be automated.

2.7.4 Poultry droppings image analysis to determine sick and healthy birds

Poultry droppings examination can be an effective way of detecting if the birds are suffering from a digestive disease. The droppings of infected birds tend to be different in texture, color, shape, and water content from normal droppings. (Wang et al,2019) developed a system that was able to classify broiler droppings as being normal or abnormal. They compared the performance of R-CNN and YOLO-V3 and found that R-CNN outperformed YOLO in classifying the broiler droppings.

2.7.5 Animal motion monitoring to detect lethargy through computer vision

In most cases, animals' and birds’ diseases manifest themselves through a lack of energy and enthusiasm, a condition known as lethargy. (Fernández et al, 2020) explored the use of computer vision to detect lethargy in pigs caused by African swine fever. In their approach, they trained a convolution neural network with stochastic gradient descent. Even though the study had a limitation in the fact that reduced motion did not correspond to animal temperature, it this not obvious that an inactive animal could be sick, understanding normal animal activity might be useful such that when this activity falls below the expected level, it could be used to infer a change in the animal health or external factors affecting the wellbeing of the animals. Even though this study was applied to pigs, it could be equally applied to other animals or poultry birds.

2.8 Research Gap

Most of the studies under review suggest the use of a convolution neural network to perform deep learning owing to it being powerful. (Kola et al,2021) used convolution neural networks in the detection of tumors in animals. They used Keras and Tensor flow to perform deep learning on MRI pictures of the brain that contain possible tumors of livestock. (Wang et al,2019) used convolution neural networks to recognize and classify broiler droppings to diagnose broiler digestive diseases, and (Cuan et al,2020) used a convolution neural network to detect chicken infected with avian influenza by analyzing chicken sound.

Each of the solutions had a specific task, for example, to detect birds with digestive disease or to detect birds with respiratory disease. To monitor poultry holistically will require that the farmer install each of the specialized systems that monitor specific aspects of the birds. This would be expensive. Furthermore, some of the solutions cannot be applied in real-life poultry monitoring. For example, A model that uses sound to classify sick and healthy birds may not be able to match the sound to the bird that produced it in cases where there are several birds in a poultry house. The same problem applies to dropping analysis. It is difficult to match the droppings to the birds that produce them. Most of the diseases in birds also manifest themselves through the general shape and posture of the birds. For example, the neck looks upright and firm for the healthy chicken while the sick one has the neck drooped and weak. The tail and back of the sick chicken also appear drooped, unlike the healthy one where the tail is firm and stands upright. Using computer vision to observe the shape and posture of the birds can be an easier way of identifying sick birds.

In the cases where classification is done using images, the models learned the features to use from the images. Some of these features include edges, ridges, corners, texture, and color. Can the models perform better if they were guided to use a specific feature like edges or ridges or corners? This question can only be answered through a scientific inquest.

2.9 Conceptual design

The conceptual architecture was guided by available technology and the objectives to be met.

2.9.1 Available technology

The technology available to analyze birds' posture to determine their health status involved training a convolution neural network by presenting several labeled images to the model. The images were first preprocessed, edge information was obtained from the images, and a new dataset of labeled images with only a single feature was created. The new dataset was used to train the neural network

2.9.2 Objectives to be met

One of the objectives to be met was to train a convolution neural network to classify images as either healthy or unhealthy and develop a user interface for farmers to use in monitoring their flock. Given this objective, the conceptual architecture shows how various components are related to one another to achieve this objective.

The following diagram shows the conceptual architecture

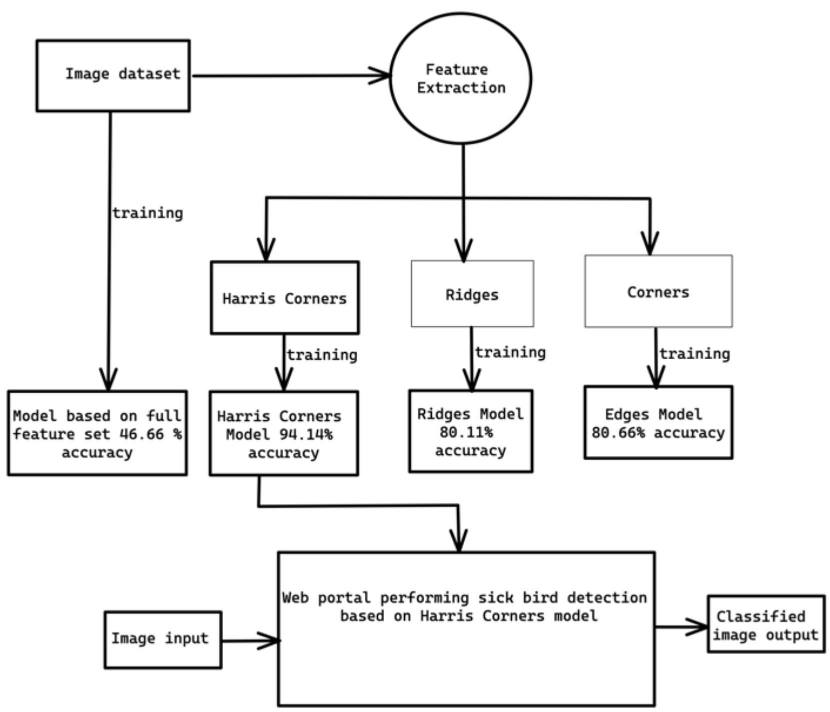


Figure 1 Conceptual design

CHAPTER THREE: METHODOLOGY

This chapter outlines the research design, the methods, and tools that were used to collect data, and the methods and techniques that were used to preprocess the data, training of the classifier models, and evaluation of the model, and eventually building of the user interface.

3.1 Research design

The research took a qualitative research design because the result is reported in a descriptive form-sick or not sick. The sick birds are highlighted in red color, and this is used to communicate to the users more descriptively. The research was also explorative because it explored the possibility of using a single feature of an image to classify birds as sick or healthy. It investigated the feature that had the strongest relationship with the bird’s health status. The general shape of the birds can be used to tell if a bird is sick or not. A chicken, hen, or broiler is probably sick if its wings, and tail stoop downwards and the neck is the wick and bent downwards. The output was also qualitative because it was a classification that can be either sick, normal, or unknown.

3.2 Creation of labeled datasets

This section highlights the steps that were taken to achieve the first objective of creating a labeled dataset. The steps involved the identification of sources of images, acquisition of the images, and pre-processing of the images to obtain the datasets.

3.2.1 Sources of images

The project required a minimum of 1000 images to train the convolution neural network. These images were obtained from a poultry farm in Manga area within Kisii county. This area was selected because of its proximity and convenience of access by the researcher. In the case of sick birds, since the images were not readily available in the farms, publicly available images were obtained from internet sources

3.2.2 image acquisition

In cases where images were available in the farms, the images were obtained using a high-resolution camera that was held in a way to capture the top view or a view that gave uniform background to make the background removal process an easy task. In cases where the images were obtained from online sources, only those images that appeared realistic were downloaded.

Camera view

The camera view was carefully selected to minimize image distortion due to the angle of inclination of the camera. Another consideration when positioning the camera was to ensure that the background is as homogeneous as possible. This was useful because it was easy to remove the background when it was homogeneous. The same camera view was consistently applied when the images were being taken just to ensure that no additional noise is introduced due to the camera view hence addressing the problem of viewpoint variation where the same object has been captured in different views which ends up confusing the model that they are different objects while indeed the different images refer to the same object. The top view was preferred because it captured most of the areas of interest. Including neck, tail, back, and wings

Beyond the camera view, the following considerations were also made.

i. Sampling rate

This refers to the number of images taken almost at the same time and same position of the object with the same camera view angle. Taking very many images of the same object leading to identical images would lead to increasing the dataset without necessarily increasing the feature set. Care was taken while taking multiple images of the same object. Subsequent images were taken after the target object has made some movement hence providing an opportunity of getting new features when the image is taken.

ii. Image resolution

While high image resolution implies high-quality images, obtaining high-resolution images always comes at a cost in the sense that they require more storage space. (1280 x 720 pixels) resolutions are common in many pieces of literature. As much as a high-resolution image implies a quality image, it is not necessarily true that higher-resolution images will always lead to better performance in training and classification using a convolution neural network.

(Shao et al,2020) studied Cattle detection and counting in UAV images based on convolutional neural networks. They used various image resolutions ad their results indicated that a resolution of 768 x 768 pixels achieved the highest detection performance. Therefore, for this study, image resolutions of 768 X 768 pixels were used

iii. Image type

While the project hoped to use PNG image format because they do not lose quality when compressed, the cameras used by default provided JPG. Converting JPG to PNG would compromise quality hence the JPG format was used.

iv. Distance between the camera and the area of interest

The distance between the lens of a camera and the object of interest determines the number of pixels in the image. A shorter distance will result in higher pixels, but it may lead to not capturing some parts while a longer distance will lead to lower pixels which might compromise the quality of the images. In this project, the optimal distance was arrived at through experimentation where several trials were made, and the best image determined the correct image-to-lens distance.

v. Class Balance in Dataset

The dataset contained two classes i.e the sick and the healthy birds. The number of images in both classes was approximately equal in number to avoid a situation where the model becomes biased in classification which infers classes with small-proportion training data less accurately.

3.2.3 Image preprocessing

A single image shot had multiple birds in it. However, to train a CNN model, each image used for training should only have one bird. To achieve this, the original image from the camera was cropped such that each image went to its file.

The following image illustrates how one image was cropped to produce 6 separate images of hens.

i. Background Removal

The images were obtained in varying backgrounds and different lighting conditions. To obtain better results, the images were cleaned to remove unwanted features. Since most of the unwanted features lie in the background, backgrounds were removed from all the images.

i. Image resizing

Image resizing was used to solve the problem of scale variation where the image of the same object exists in multiple sizes. At the same time, having smaller images in size guarantees faster processing because resizing reduces the picture elements that need to be processed. The images were resized to 224 pixels by 224 pixels

ii. Data Augmentation

Data augmentation was done to increase the dataset. For every single image, rotation transformation was applied on an axis between 10 and 3590 with each rotation of 900. This rotation was done using the Keras ImageDataGenerator class where rotation angle 900 was used. However, rotating an image on the same axis can lead to some pixels not changing position, hence introducing positional bias. To avoid this bias, the rotations were coupled with horizontal and vertical translations.

Figure 2 Original image before Rotation and Horizontal and Vertical Translation

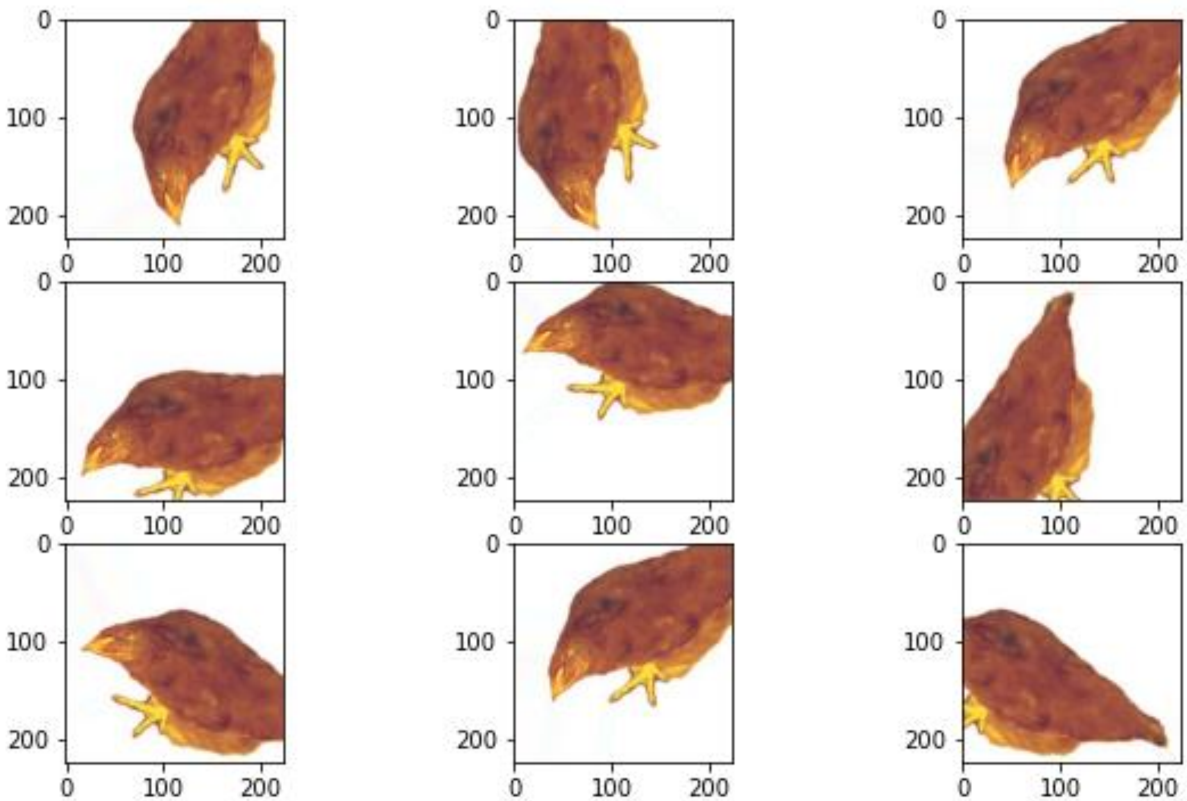


Figure 3 Different images obtained as a result of Rotation and Horizontal and Vertical Translation

3.2.4 Feature Extraction

Image features were extracted using the following steps.

i. The first step which involved image blurring was done using OpenCV's GaussianBlur function with a kernel size of 13 by 13 to reduce noise levels in the images.

ii. The second step involved converting the blurred image to grayscale using OpenCV cvtColor function.

iii. The third step histogram equalization to enhance contrast in the images by ensuring that areas of an image with low contrast gain higher contrast. OpenCV equalizeHist function was used to achieve this. The function takes a grayscale image as an input. Below is an example of a grayscale image that appeared washed out but was improved using histogram equalization?

Figure 4 Grayscale of the washed-out image

Figure 4 is the grayscale representation of image 3. Since color as a feature is not useful in detecting sick or healthy birds, gray scaling was performed to reduce the color space for better performance.

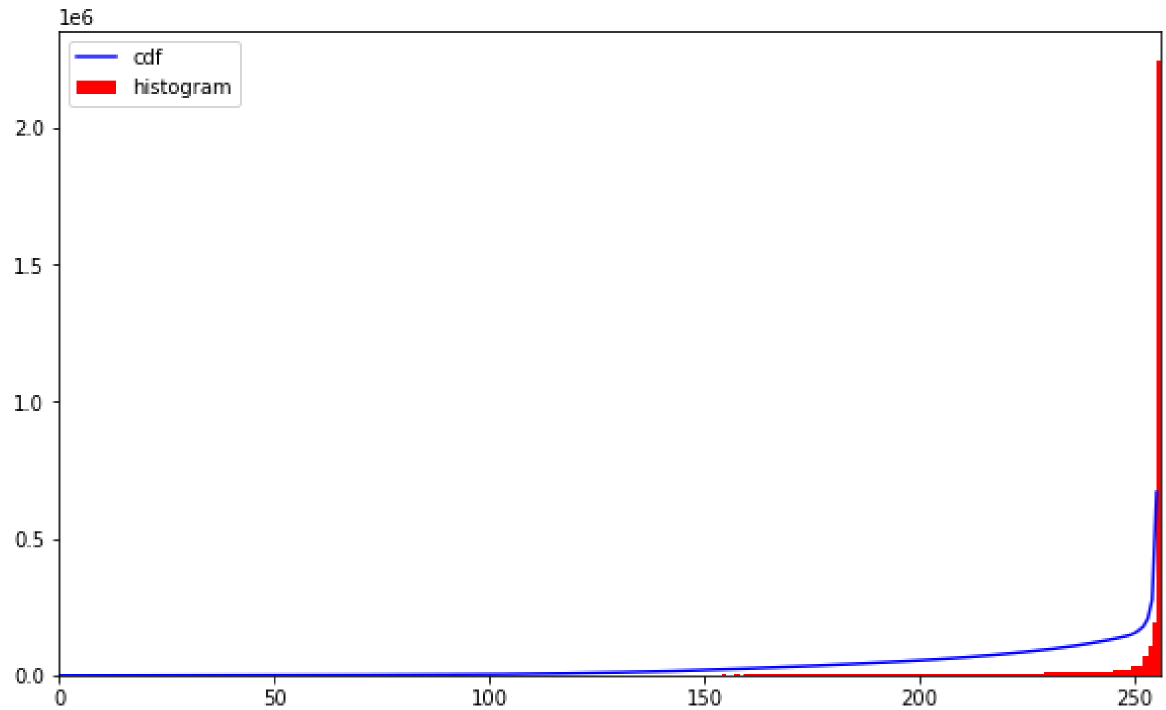


Figure 5 Histogram of the grayscale image

As shown on the diagram, Pixel intensity starts to increase from 150 to 250 but the increase is more between 200 and 250. Pixel intensity is near zero from 0 to slightly above 150. The distribution is skewed towards the higher pixels.

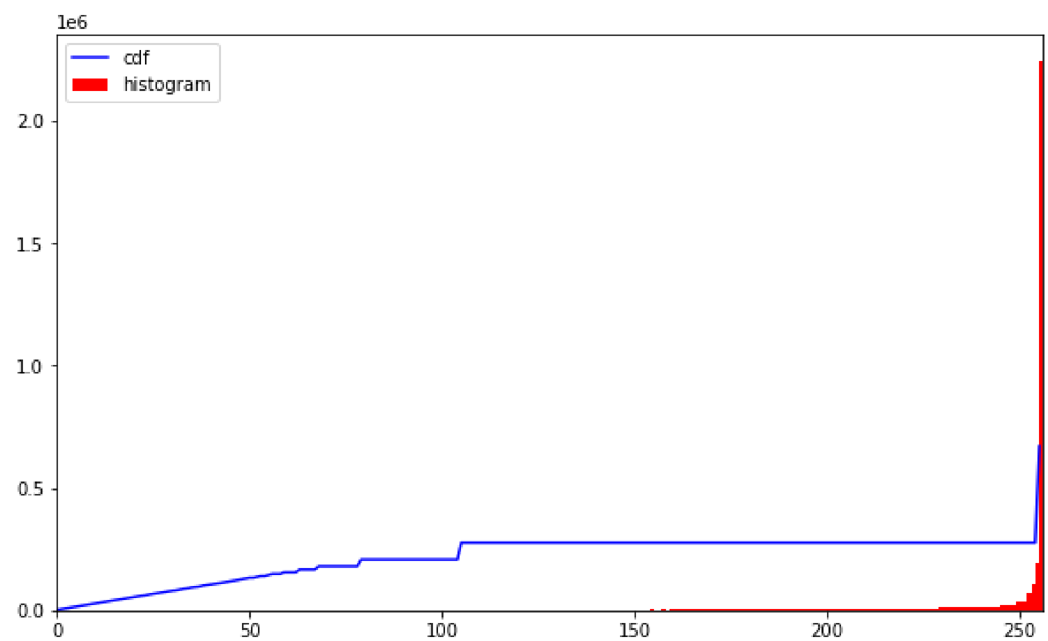


Figure 6 Histogram of the image after Histogram equalization

After Histogram equalization as can be seen from the above diagram, there is a general increase in pixel intensity from zero and pixel intensity above 100 has been averaging almost the same value

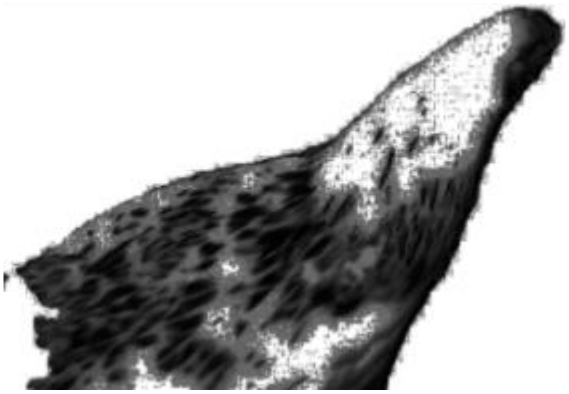
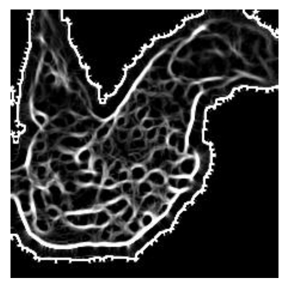
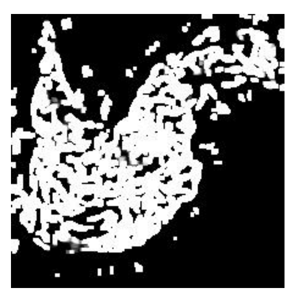


Figure 7 Grayscale image after Histogram equalization

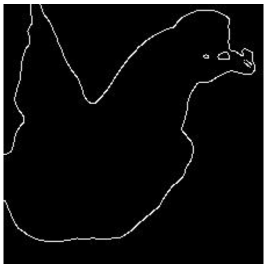
iv. Ridges were extracted using the RidgeDetectionFilter_create function inside the ximgproc package of the OpenCV library. The extracted ridges were stored in a separate folder.



v. Harris corners were extracted using cornerHarris function of OpenCV library using a kernel window of 5 by 5 and the output was stored in a separate folder.



vi. Canny edges were extracted using the Canny function of the OpenCV library and the outputs were stored in a separate folder



3.2.5 Training of a convolution neural network

This section highlights the model that was trained and tested. The training was done by first annotating the images. The annotated images acted as examples from which the model learned to classify the birds as sick or not sick.

Two models were trained. The first model was trained to detect if the object in an image is a bird or not while the second model was trained to detect a sick bird given shape and posture information. In both cases, image annotation was done to obtain a labeled dataset. In the first case, the task was object detection where the object is a hen, whether sick or not while in the latter case, the task was to distinguish between two objects by feature analysis.

In the first case, image labeling was done using LabelImg which is a graphical annotation tool written in python, that is used to label images for object detection and object classification tasks.

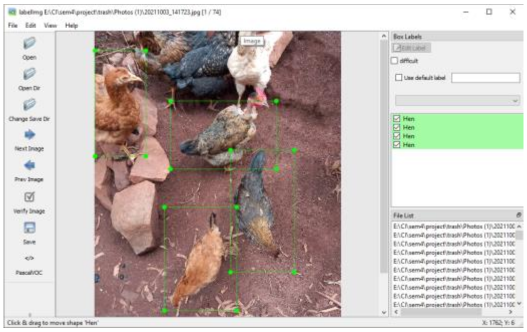


Figure 8 Image annotation using LabelImg

In Image 8 above, there are hens and stones as objects in the image. Annotation was done to only identify hens and ignore the stones. The annotations were then saved in PASCAL_VOC format and later converted to YOLO format.

In the second case, edges, ridges, and Harris corners were extracted from the images of both sick and healthy birds. Each feature for both sick and healthy birds was stored in separate folders and later used to train models to detect sick and healthy birds based on the three features. Four different datasets were obtained. The first dataset was obtained from images of sick and healthy hens without extracting any feature as shown in figures 9 and 10 below.

Figure 9 Sample healthy hens

Figure 10 Sample sick hens

The second dataset was obtained by extracting edges from the images of sick and healthy hens as shown in figure 11 and 12

Figure 11 Sample healthy hens based on edge information.

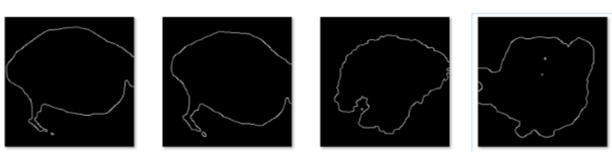


Figure 12 Sample sick birds based on edge information.

The third dataset was obtained by extracting Harris Corners from the images of sick and healthy hens as shown in figures 13 and 14.

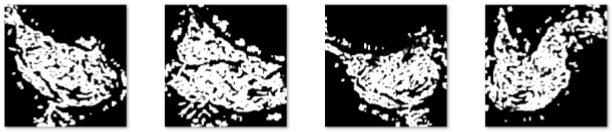


Figure 13 Sample healthy hens based on Harris Corners

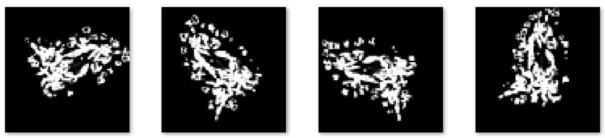


Figure 14 Sample sick hens based on Harris Corners

The fourth dataset was obtained by extracting Ridges from the images of sick and healthy hens as shown in Figures 13 and 14.

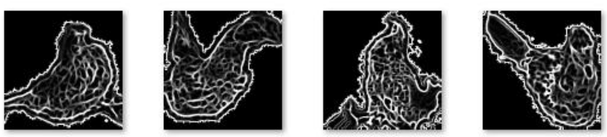


Figure 15 Sample healthy hens based on Ridges.

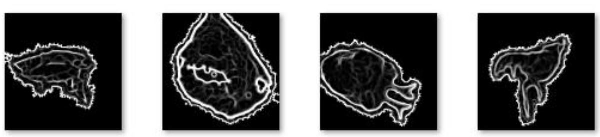


Figure 16 Sample sick hens based on Ridges.

Four convolution neural networks based on the extracted features were trained and tested. Each of the datasets was used to train a Keras sequential model such that there were three Models whose performances were compared. Each of the models was tuned with the same parameters during training such that any difference in the accuracy of training was solely influenced by the type of dataset used. Each of the datasets was used to train a Keras sequential model such that there were three Models whose performances were compared. Each of the models was tuned with the same parameters during training such that any difference in the accuracy of training was solely influenced by the type of dataset used.

3.2.6 Evaluation and testing of the convolution neural network.

The models were evaluated based on performance during training and performance on unseen data. Performance during training: For each data set, the data was split into training and testing datasets in the ratio 80:20 respectively. The number of images in the test dataset was a random selection from the entire images available. The models were then trained on the training dataset. The trained models were subjected to a test dataset and the performance was measured in terms of accuracy of classification which is given by the total number of images that were correctly classified expressed as a percentage. Figure 17 shows the results of each model based on a feature.

Performance on unseen data: One hundred images previously unseen by the models were subjected to the models. The performance of the models was then determined based on the number of healthy hens that were predicted as healthy, the number of healthy hens that were predicted to be sick, the number of sick hens that were predicted to be sick, and the number of sick hens that were predicted to be healthy. The result was recorded on a confusion matrix.

The table below summarizes the performance of all four models. Figure 18 Comparison of model performance

Key:

P: Precision – When the classifier predicts that the hen is sick, how often is it correct?
A: Accuracy – In overall, how often is the classifier correct?
MR: Misclassification Rate – In overall, how often is the classifier wrong?
TPR: True Positive Rate – when the hen is sick, how often does the classifier predict it to be sick?
FPR: False Positive Rate – when the hen is sick, how often does the classifier predict it to be healthy?
TNR: True Negative Rate – when the hen is healthy, how often does the classifier predict it to be healthy?
FNR: False Negative Rate – When the hen is healthy, how often does the classifier predicts it to be sick?

3.2.7 Conclusion

The study was able to demonstrate that it is possible to develop a computer vision system that can detect sick hens by their general appearance. This solves the problem of not having to install multiple systems each monitoring specific aspects of the hens which will make the overall monitoring of the birds an expensive task. Furthermore, the study shows that in a classification problem where classes of the objects are very similar, Harris corners are better descriptors and can successfully be used to distinguish between the features.

3.2.8 Further Work

This study focused on comparing the performance of ridges, edges, and Harris corners. It is still not clear whether better descriptors exist that can perform better than the Harris corners in a classification task that resembles this one. Further work can be done to establish this.

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