DEVELOPMENT OF MACHINE LEARNING ALGORITHM USING COMPUTER VISION FOR PREDICTIVE ANALYTICS IN A BATTERY CAGE POULTRY SYSTEM

***Okolie U. C.[1], Iloh J.P.I.[2], and Mbachu C. B[3].**

[1]Electronics Development Institute (ELDI), Awka, Anambra State, Nigeria
[2,3]Department of Electrical/Electronic Engineering, Faculty of Engineering, Chukwuemeka Odumegwu Ojukwu University, Uli, Anambra State, Nigeria

*Corresponding author: okolieuc@gmail.com

ABSTRACT

In order to protect animal welfare, increase production, and lower the frequency of disease outbreaks, the growing poultry industry particularly in battery cage systems requires advanced monitoring technologies. This study presents the development of a machine learning algorithm using computer vision for predictive analytics, early disease detection, and real-time behaviour assessment in battery cage poultry systems. Convolutional neural networks (CNNs) were used to scan high-resolution video streams in order to identify physical symptoms that may indicate health issues and identify aberrant behaviours. To improve the precision of decision-making, additional parameters were analyzed, such as feeding patterns, temperature, and movement metrics. While predictive algorithms foresee possible disease spread and productivity trends, the system uses supervised learning to categorize actions and identify anomalies. When compared to traditional methods, the computer vision method showed significant improvements in behavioral monitoring and early disease identification, offering a scalable, non-invasive option for smart poultry farming. Through automation and data-driven insights, this innovation promotes proactive poultry management methods, enhancing animal welfare, and supports sustainable poultry production.

Keywords: Convolutional neural network, machine learning, computer version, battery cage poultry

1.0 INTRODUCTION

The rapid growth of the poultry industry has created a strong demand for modern technologies that can improve productivity, reduce losses, and enhance animal welfare (Fatoki *et al* 2024). Traditional monitoring methods in battery cage poultry systems rely heavily on manual observation, which is labor-intensive, prone to human error, and often unable to provide real-time insights. As a result, famers may fail to detect early signs of disease, abnormal behavior, or environmental stress that can negatively impact flock performance.

Recent advances in machine learning and computer vision have opened new opportunities for automated, data-driven poultry management (Eko & Sutrisno, 2023). Machine learning algorithms, when combined with image and video data captured by cameras, can analyse bird behavior, detect deviations from normal patterns, and predict potential health challenges before they escalate (Ananya, 2021).

By integrating these intelligent systems with environmental sensors and farm management platforms, it becomes possible to generate predictive analytics, such as early disease detection, behavioural changes due to stress, feed or water intake abnormalities, and productivity trends (Elbarrany *et al*, 2023). Machine learning algorithms can analyze images from surveillance cameras to detect diseases such as avian influenza and mycoplasmas with high accuracy, reaching up to 99.94% in some cases (Doan et al., 2022). This approach not only enhances decision-making but also reduces mortality, increases efficiency, and promotes better welfare standards ("Exploring Deep Learning for Detection of Poultry Activities towards an Autonomous Health and Welfare Monitoring in Poultry Farms", 2023).

Therefore, the development of a machine learning algorithm using computer vision for behavior analysis, disease detection, and predictive analytics in battery cage poultry systems represents a significant advancement toward precision livestock farming. It provides a scalable, real-time, and cost-effective solution that supports farmers in maintaining healthier flocks, optimizing production, and improving overall farm sustainability (Eric *et al.,* 2018).

2.0 RELATED WORKS

According to Kalita *et al*. (2024), Capitalizing on data from physiological and behavioral traits like movement, vocalization, body temperature, and excreta, AI algorithms can detect indications of illness and pathological conditions, which means strengthening disease management and bringing down economic losses. High-precision image and video processing, non-invasive monitoring, the use of thermal imaging, and accurate tracking of poultry to spot health issues are some of the crucial developments that have also aided in analyzing stress and other abnormalities. Incorporating new-age technologies into feasible, applicable, and economical diagnostic tools that have the potential to transform poultry well-being, enhance the welfare of poultry, and upgrade production as well as handling processes is discussed here (Victoria *et al*., 2025). The upcoming prospects include global partnerships, better data analytics, and extended research or studies for the management of diseases and behavioral anomalies in all poultry species. The collaboration of AI, machine learning, and biotechnology holds colossal promise for the poultry sector, guaranteeing food safety and ensuring public health (Fang *et al*., 2020).

Elbarrany *et al*., (2023), aimed to develop a comprehensive understanding of the various factors contributing to abnormal behavior patterns and the methods for effectively monitoring and detecting these behaviors. By identifying and addressing issues related to illness, stress, or discomfort at an early stage using the proposed system, farmers can implement targeted interventions to improve the overall well-being of the birds, leading to enhanced production efficiency and profitability. Furthermore, this research contributes to the development of sustainable poultry farming practices, protecting public health, and safeguarding food safety, highlighting the significance of abnormal behavior analysis in the poultry industry (Rasheed *et al*., 2022).

This paper proposed a computer vision-based system that monitors and analyzes the chickens' behaviors in poultry farms. The system takes video input and segments them into 10-second segments. The proposed system achieved an accuracy of 96.43% using a convolutional neural network for heat maps classification. Doan *et al*., (2022) introduced several results achieved in the research and construction of an automatic system for early detection of various poultry diseases by computer vision technology, using artificial intelligence to analyse images from surveillance cameras. Fatoki *et al*., (2024) reviewed recent advancements in computer vision methods for detecting behaviors in livestock such as cattle with an emphasis on behaviors critical for health, welfare, and productivity. They investigated the development of both traditional computer vision and deep learning techniques for image segmentation, identification, and behavior recognition. The review explored the development of research trends in livestock behavior recognition, focusing on improvements in reliable identification algorithms (Olanrewaju *et al*., 2024)., the analysis of behaviors at different growth stages, the measurement of behavioral data, and the design of systems to evaluate welfare, health, growth, and development.

3.0 SYSTEM DEVELOPMENT AND IMPLEMENTATION

3.1 Image Preprocessing

To enhance the model, it entails resizing (changing the image's height and width) and augmentation (transforming photos to broaden the dataset's diversity). Utilizing Open CV's IMG read function, the test images are resized to 150 x 150 pixels. Equation 3.1 is then used to normalize the images. This procedure guarantees that the image pixels are within the [0, 1] range and modifies the image's brightness as shown in equation 1.

$$img_p = \frac{img}{255} \qquad (1)$$

3.2 Mathematical model

The targeted operation of the poultry birds was taken into consideration when modelling the k-fold CNN architecture. One convolutional layer, one max pooling layer, one flattening layer, and two dense layers separated by a dropout layer comprise the CNN layers. K-fold cross-validation, which divides the original sample into k equal-sized subsamples at random, is the method used to train the CNN model. Out of the k subsamples, k-1 subsamples are utilized as training data, and one subsample is kept as validation data to test the model. Next, k times through the cross-validation procedure, the validation data is taken from each of the k subsamples exactly once. After that, an estimate is created by averaging the k outcomes. This procedure is used to lessen the training models over fitting as shown in table 1.

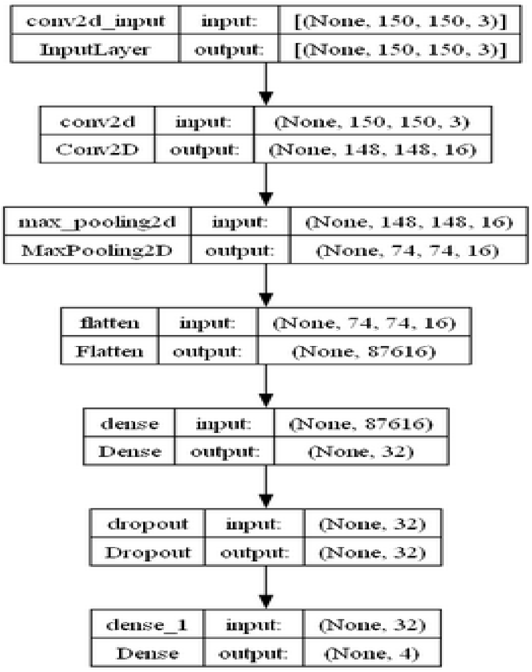

Figure 3.1 Structural representation of the custom K-Fold CNN model used for chicken bird classification from images model

The model utilised in this work has the general structure depicted in Figure 3.1. The k-fold cross-validation function is utilised to loop over this model five times. Feature extraction and classification are the two categories (pooling layer and convolutional layer) into which the CNN layers can interact with inputs.

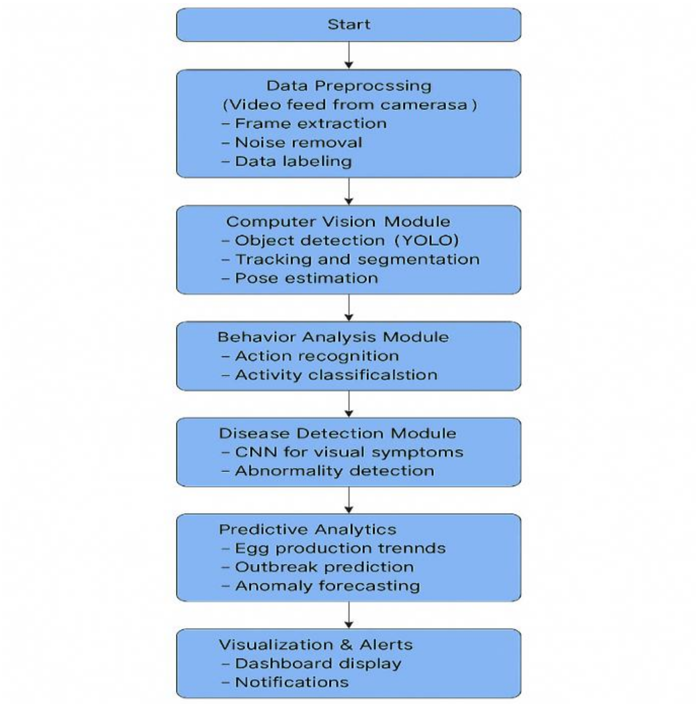

Figure 3.2: Flow Chart of the CNN Layer

3.3 Convolutional Layers

The model fed coloured images with 150x150x3 pixel resolution. 16 3x3 filters are applied to the input image, resulting in 16 feature maps in the first convolution layer. Using the filter, the features are extracted during the convolution process. Equation 2 and 3 illustrates how the convolution operation between the input image (M) and the filter (T) represents the feature map (F).

$$F[i,j] = (M * T)_{[i,j]} \tag{2}$$

The ij-th entry of the feature maps is as shown in equation 3

$$f[i,j] = \sum_{x}^{h_m} \sum_{y}^{w_m} \sum_{z}^{n} M_{[x,y,z]}\, T_{[i+x-1,\ j+y-1,\ z]} \tag{3}$$

3.4 Pooling Layers

The maximum activations of these 16 feature maps with a stride of 3×3 pixels are selected in the max pooling layer using a pool size of 2×2 pixels. The size of the feature maps is decreased as a result of the stride, which shows how far the pooling matrix goes for each pooling step. By deleting the less important features (the minimum values), the pooling layer makes sure that the most important details (the maximum values) are retained as shown in equation 4

$$P = \phi_p(M * T) \tag{4}$$

Where ϕ_p is the pooling function. The dimension of the pooling layer is gotten from the formula in equation 5, where $h_m \times w_m$ represents the dimensions of the input, $h_t \times w_t$ represents the dimensions of the filter, s is the stride length and n is the number of channels in the input.

$$\dim of\ P = \left(\frac{h_m+1-h_t}{s}\right) \times \left(\frac{w_m+1-w_t}{s}\right) \times n \tag{5}$$

3.5 Classification

The task of this CNN part is to categorize the features of the extracted images into any of the four classes that the model has created. It is made up of three layers: the thick layer, the dropout layer, and the flattening layer.

(i) Flattening Layer

To facilitate computing, the convolutional and pooling layers' stacked output is reduced to a 1-dimensional shape in the flattening layer, which comes first in the classification process. It sends the output to the dense layers.

(ii) Dense Layer

The first dense layer has 32 classes and the second one (the last layer of the CNN) has four classes (i.e., the classification in the dataset). The mathematical operation of the dense layer is as given in equation 6 where ϕ_d is the activation function of the dense layer, P is the input to the layer, w is the kernel and b is the bias of the layer.

$$z = \phi_d(\textstyle\sum_i w_i P_i + b) \qquad (6)$$

(iii) Dropout Layer

It is positioned between the two dense layers so that the most noticeable characteristics can be chosen for categorization. It has a value of 0.5 as shown in equation 7. Therefore, before determining the last layer's weights, the dropout chance is multiplied by the weights from the preceding layer.

$$w_i = w \, x \, 0.5 \qquad (7)$$

3.6 Activation Functions

With the exception of the final dense layer, which utilizes a Soft max activation function, all of the layers use the ReLU activation function. In this work, the conventional function that chooses an element-wise maximum of 0 and the input data is called ReLU. It computes as shown in Equation 8, where c is the output at the layer where the activation function is applied, and imposes a bias value, b, on the convoluted output of each layer.

$$c = \phi_a(M * T + b) \qquad (8)$$

Since the Softmax function provides a vector as a probability value and its output vector's elements result in 1, it functions as a classifier and is employed in the final dense layer. For the model in this instance, there are four probability classifications. Equation 9 is used to perform the Soft max activation, where z is the output of the preceding dense layer.

$$softmax(z) = \frac{\exp(z)}{\sum \exp(z)} \qquad (9)$$

3.7 Model Compilation

After the architecture and activation functions of the model is decided and the code written, the model is compiled and the metrics is evaluated via its performance.

Because the Adam optimizer is computationally efficient and can update the network's weights iteratively without the need for tuning, it was utilised for optimisation in this work. The Adam optimizer is calculated with equations 10 and 11, where a_{dW} is the exponential weighted average of the previous gradients, b_{dW} is the exponential weighted average of the previous squares of gradients, β_1, β_2 are tuned hyperparameters, $\frac{\partial H}{\partial W}$ is the derivative of the loss function with respect to the weight.

$$a_{dW} = \beta_1 a_{dW} + (1 - \beta_1)\frac{\partial H}{\partial W} \qquad (10)$$

$$b_{dW} = \beta_2 b_{dW} + (1 - \beta_2)\frac{\partial H}{\partial W} \qquad (11)$$

To reduce loss and enhance the model, the Loss function, Categorical Cross Entropy, computes and modifies the model's weights during training. The expected output (x), the CNN estimation (q(x), and the likelihood of correctly classifying the picture (p(x)) are represented in equation 12.

$$H(p, q) = -\sum p(x) \log q(x) \qquad (12)$$

3.8 Model Training

The training of the CNN layers is the next stage of the job in order to obtain an appropriate output. This is achieved with the model. Fit () function which "fits" the neural network layers with the image data for inferencing of related features. The input data (training set variable), the number of training iterations (epochs=25), and the validation data (validation data variable) are the parameters that this function needs in order to train the model efficiently. Appendix A contains the code that carries out the model training.

Table 2: A description of the model that includes the form of the input and output images for each CNN layer, along with the total number of parameters that were learned.

Model: Sequential

Layer (type)	**Output Shape**	**Param #**
Conv2D	(None, 148, 148, 16)	448
MaxPooling2D	(None, 74, 74, 16)	0
Flatten	(None, 87616)	0
Dense	(None, 32)	2803744
Dropout	(None, 32)	0
Dense	(None, 4)	132
Total trainable params	28043224	

3.9 Metrics of the Mode

Certain criteria (metrics) can be used to access a deep learning classification model. These metrics, which may be computed using four values taken from the confusion matrix as listed in equation 13, 14, 15 and 16, are Accuracy, Precision, Recall, and F1 Score. The following metrics are calculated using this matrix, which has values labelled as True Positive (TP), False Positive (FP), False Negative (FN), and True Negative (TN):

$$\text{Accuracy} = \frac{(TP+TN)}{TP+TN+FP+FN} \times 100 \quad (13)$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad (14)$$

$$\text{Recall or True Positive Rate} = \frac{TP}{TP+FN} \quad (15)$$

$$\text{False Positive rate} = \frac{FP}{FP+TN} \quad (16)$$

4.0 RESULTS AND DISCUSSION

4.1 Accuracy Graph

The accuracy measures the percentage of your data that was correctly classified (TP and TN) out of all the predicted data. The accuracy graph (on the left) indicates a maximum value of over 95% for both the test and validation data

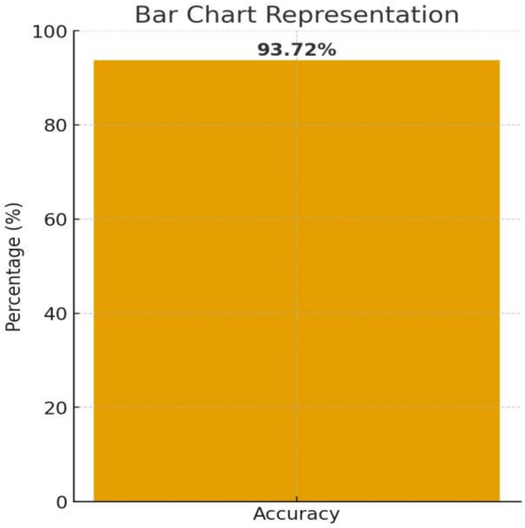

Figure 4.1: Accuracy Graph

4.2 Precision Graph

The precision value shows that the model is able to correctly classify 94.52% of correctly positive labels (TP) out of all the predicted positives (TP & FP)

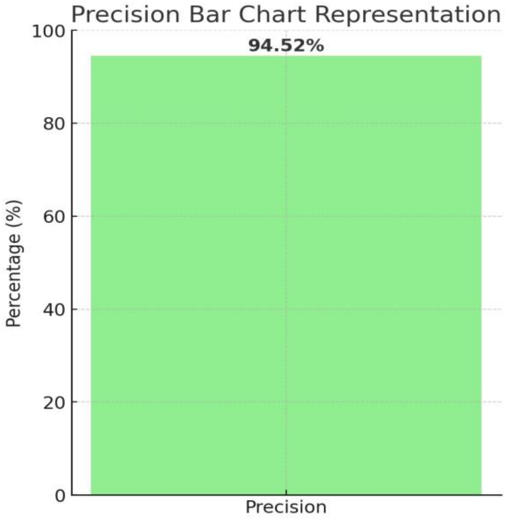

Figure 4.2: precision graph

4.3 Recall Graph

The recall value shows that the model is able to correctly classify 97.88% of correctly positive labels (TP) out of all the actual positives (TP & FN).

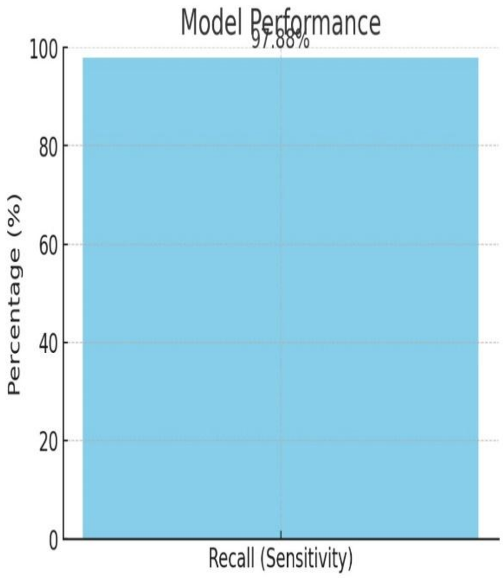

Figure 4.3: Recall Graph

4.4 F1 Score

This is the harmonic mean of precision and recall. It balances the trade-off between these two metrics, providing a single value that reflects both, as shown in Figure 4.4.

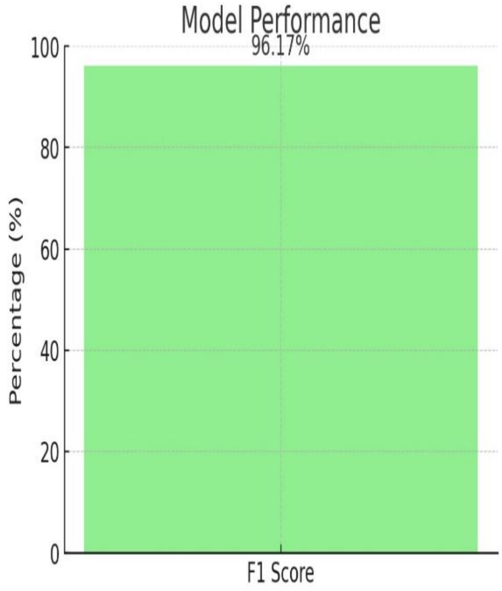

Figure 4.4: F1 score graph

4.5 Model performance

The specificity of the model is given by 76.41% which on the average was certified okay as shown in figure 4.5.

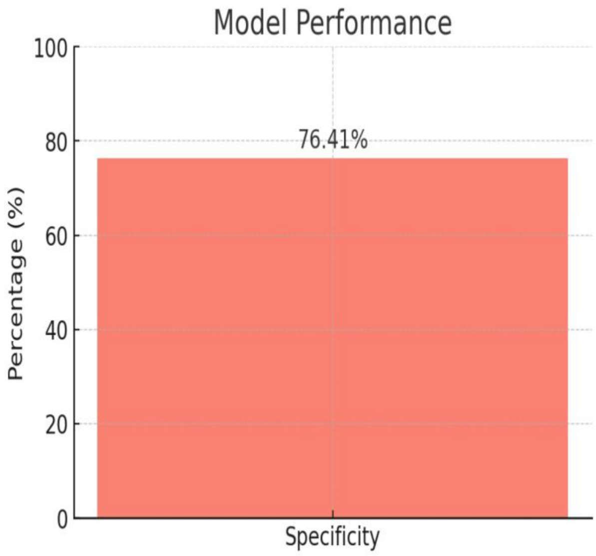

Figure 4.5: model performance

4.6 False Positive Rate

A **false positive** in computer vision is a **"ghost detection"**—the model's confident but incorrect identification is valued at 23.59% as shown in figure 4.6.

Figure 4.6: false positive rate

5.0 CONCLUSION

The integration of machine learning algorithms with computer vision in battery cage poultry systems marks a significant advancement in precision livestock farming. This study successfully demonstrated the potential of such technologies to automate behaviour analysis, detect early signs of disease, and provide predictive insights into flock health and productivity. By leveraging real-time video data, the developed system can monitor critical behaviours such as feeding, drinking, aggression, and lethargy, while simultaneously identifying abnormal patterns that may indicate disease onset. The application of predictive analytics further enhances decision-making by forecasting potential health issues and productivity trends, allowing for proactive intervention. This not only improves animal welfare but also optimizes resource use and operational efficiency. Overall, the developed system represents a scalable and cost-effective solution that can transform traditional poultry management into a data-driven, intelligent process. Future work could involve expanding the model to accommodate other poultry housing systems, incorporating additional environmental sensors, and enhancing model accuracy with larger, more diverse datasets.

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