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Early Detection of Disease in Chicks Using CNN on Bangkok Chicken Health

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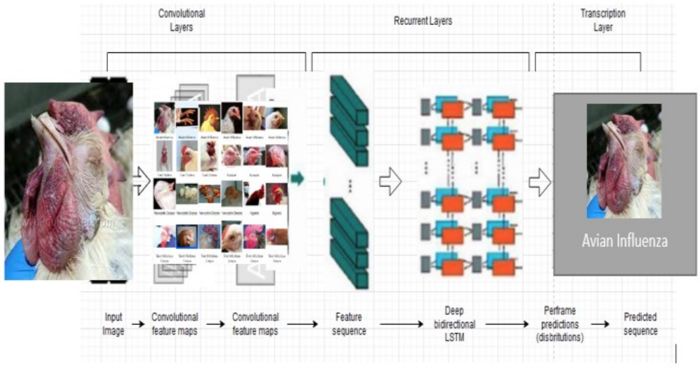
ABSTRACT



Bangkok Chicken (Gallus Gallus Domesticus) is a type of chicken in Indonesia that has a high source of protein and supports the community's economy. The growth and development phase of chicks is a critical period because chicks are very vulnerable to attacks by infectious and non-infectious diseases. These diseases can cause high mortality rates and cause significant economic losses for farmers. This study aimed to investigate the potential for using CNN technology in the early detection of disease in Bangkok chicks in the Ponorogo district. As an artificial neural network, CNN can recognize patterns in visual data with high accuracy. The use of CNN technology in the agricultural sector, including animal husbandry, has shown promising results in supporting early disease detection systems in livestock. This study aims to investigate the potential of using CNN technology in the early detection of disease in Bangkok chicks in the Ponorogo district. By processing visual data from chicken images, CNN will be trained to identify early signs of disease in chicks. The result of this research is that this research can help maintain the availability and security of animal food supplies, which is an essential component of overall food security. In addition, by reducing losses caused by disease, this research can contribute to sustainable agriculture by ensuring the continuation of stable and sustainable animal food production.

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1. INTRODUCTION

Demand for livestock products increases yearly, along with an increased population and scientific and broader public awareness of the importance of consuming nutritious food [1]. Increasing public understanding of the importance of consuming nutritious food is one of the challenges in animal husbandry and agriculture today to meet nutritional and nutritional needs. In the world of agriculture, especially chicken farming, it is one of the economic sectors that plays a vital role in providing animal protein food sources for the community so that it will meet the community's nutritional needs. Therefore, the growing livestock industry will help optimize society's dietary needs.

Bangkok chicken (Gallus gallus domesticus), one of the popular poultry varieties in Indonesia, has become the leading choice for breeders to increase the productivity and quality of livestock products [2]. However, the Bangkok chicken farming industry faces various challenges, especially those related to the health and welfare of chickens, which will affect the yield and quality of the harvest. To improve the production quality and health of Bangkok chickens, information and communication technology has excellent potential to provide practical solutions. One technology that is attracting attention is CNN Technology or Convulsion Neural Network. CNN is an artificial neural network that can accurately process and recognize patterns in images or visual data [3].

Deep Learning has become a hot topic in Machine Learning because of its significant capabilities in modeling complex data such as images and sounds [4]. The deep learning method currently has the most important results in image recognition, called CNN Technology. CNN Technology is a deep learning method capable of carrying out a widespread and precise independent learning process for classification. This is because CNN tries to imitate the image recognition system in the human visual cortex to process image information . Therefore, this method can be used to help develop a disease classification system in chickens on farms. Deep learning and machine learning are two key terms in artificial intelligence that have received significant attention recently [5]. Deep learning is a subfield of machine learning that aims to enable computers to derive complex and in-depth representations from data. This is achieved through highly complex neural networks, known as deep neural networks, which can learn the most relevant features from complex or unstructured data.

On the other hand, machine learning is a broader scientific discipline that allows computers to learn from data and make decisions or predictions without being explicitly programmed. By using algorithms and statistical models, machine learning will enable computers to identify hidden patterns in data and make valuable decisions or predictions. Therefore, a clear understanding of these concepts is essential in understanding the recent advances in artificial intelligence and its applications in various domains [6].

CNN technology has three main stages in object processing: convolutional layers as object translation features. There is a pooling layer to reduce or reduce the dimensions of an image to those that have been filtered. The complex process of the CNN method means many stages in image processing, so the program is very complex and must have adequate hardware. The hardware often used for computer vision projects is a Raspberry Pi; this tool can be used as a mini computer that loads programs and installs other components. The CNN method also requires hardware to have reliable and high specifications. Raspberry Pi 4 model B microcomputer so the running process can be carried out correctly [7][8]. After the object can be detected using the CNN Technology method on the webcam camera, the process will continue to the output process.

Several previous studies observing plants and other livestock have succeeded in monitoring particular objects using PIR sensors for input, so this tool can have the feature development of making the capture input in the form of a webcam camera with image processing for object detection. The research utilizes CNN technology to classify images, so it is beneficial for detecting diseases in chickens. The VGG16 model in the CNN method first appeared in 2014; this model consists of 5 convolution and pooling layers ending with a fully connected layer [9]. This model has a large number of parameters, namely 138 million parameters. Meanwhile, DenseNet appeared in 2016; this model differs from VGG16 because it has far fewer parameters, namely 8 million. This model utilizes each initial layer, which continues to be connected to the next layer until the final layer so that all the characteristics studied at the beginning continue to be used until the end [10]. Providing more context to the existing literature can significantly strengthen the importance of the proposed research in improving the early detection of chicken diseases using Convolutional Neural Networks (CNN).

First, by identifying and outlining gaps in the literature related to the early detection of chicken diseases, this study can demonstrate its unique contribution to filling the discovered knowledge gaps. The proposed research can justify its relevance in an explored scientific context by emphasizing areas where previous research has been limited or not investigated adequately [11]. Second, giving context to the existing literature can also help highlight the practical relevance of the proposed research in the livestock industry. By referring to the latest findings or trends in related fields, this research can show the potentially significant impact of research results in improving the health and welfare of chickens and operational efficiency in chicken farming.

This may increase interest and support for the proposed research from various stakeholders, including breeders, animal health experts, and policymakers [12].

Additionally, by placing the proposed research in existing literature, this study can show how it contributes to conceptual and methodological developments in chicken disease detection. By referring to existing theories or methodological approaches, the proposed research can show how it expands our understanding of new ways to detect disease in chickens more quickly and accurately [13]. Thus, this research helps increase awareness of the importance of early detection of chicken diseases and offers innovative solutions that can improve livestock health and production efficiency in the livestock industry.

This research aims to develop an early detection system for diseases in Bangkok chicks, such as bird flu (avian influenza), fowl cholera, ringworm, Newcastle disease, snoring, and snot infectious coryza. This disease is detected using CNN Technology, and initial symptoms usually include discharge from the eyes and nose, swelling of the face and head area, diarrhea, coughing, and so on [14]. This method utilizes artificial intelligence to analyze images of the health condition of chickens and can automatically detect signs of disease in chickens.

Using CNN Technology technology, we can identify diseases in Bangkok chickens earlier. This allows chicken owners to take preventative or treatment measures more quickly, improving overall health and productivity [15]. Thus, the title highlights the importance of modern technology in chicken rearing and farm welfare. Detecting chicken diseases in this application explains the classification of chicken diseases in photos or image processing with five disease classifications: Avian Influenza, foul cholera (Ringworm), Newcastle Disease, Smoking, and Snot Infectious Coryza. We can identify diseases early and take appropriate action using CNN Technology technology for early detection. This helps improve the overall health of chickens and minimizes losses in farming. VGG16 and DenseNet models are two convolutional neural network (CNN) architectures well known for their outstanding performance in image recognition and object classification tasks. These two models are relevant to research on early detection of chicken diseases using Convolutional Neural Networks (CNN) because of their ability to extract complex features from images with high accuracy. In this research, using the VGG16 and DenseNet models allows the identification of visual patterns related to chicken disease symptoms that may be difficult to recognize by the human eye or by simpler CNN models. The main contribution of using these models in research is increasing accuracy in detecting chicken diseases by analyzing the resulting images. By leveraging features learned by VGG16 and DenseNet models from large training datasets, this research can achieve a high level of accuracy in identifying disease symptoms in chickens, increasing the effectiveness of early disease detection and the ability to prevent the spread of disease in chicken populations [16]. Therefore, the use of the VGG16 and DenseNet models makes a significant contribution to the research title by increasing the ability of the CNN model to recognize and classify disease events in chickens more accurately and quickly.

Research limitations Dataset Size The dataset size may limit this research. A more significant amount of data can improve the accuracy of the CNN model. Therefore, it is necessary to expand the dataset for more representative results. Data Variability Limitations in the variety of Bangkok chicken images may affect model performance. If a dataset only includes certain conditions, the model may not be able to recognize rare diseases or variations in symptoms [17]. Preprocessing: This research did not use any preprocessing before training the model. However, preprocessing, such as normalization, data augmentation, and image cleaning, are essential to improve model performance in real-world situations. Generalization: A trained CNN model may perform well on the training dataset but may need to perform better on new data. Cross-dataset validation and testing in different environments must be carried out to measure the model's generalization. Reliance on Visual Data: CNN can only recognize diseases based on visual information from images. If other factors influence chicken health (e.g., environmental, nutritional, or genetic factors), this model may not be able to identify them comprehensively [18]. Computational Cost: Training CNN models requires significant computing resources. Limitations in access to powerful hardware can limit the scale of research. Dependence on Image Quality: Blurry or fuzzy image quality can affect model performance. If the image is not clear, disease detection may be inaccurate. Technology Limitations: Although CNNs are effective, this technology still has limitations. For example, the model may have difficulty recognizing subtle or complex symptoms.

Early detection of disease in livestock, including chickens, has significant implications for sustainable agriculture, food security, and economic development [19]. First, early disease detection supports sustainable agriculture principles by maintaining livestock health and welfare. Preventive measures and appropriate handling can reduce the risk of disease spread, avoiding potential reductions in animal production and negative impacts on overall animal health. Second, early detection of disease in chickens supports food security by ensuring the availability and safety of animal food supplies. By reducing the risk of disease that can disrupt the production of eggs, meat, or other animal products, livestock can maintain stable production levels, prevent food shortages, and increase food security locally and globally. Third, early detection of disease in livestock also has a positive impact on economic development by increasing livestock operations' productivity and efficiency. By reducing losses caused by disease, livestock farming can maintain its profitability and positively contribute to the local and national economy. Thus, early detection of diseases in chickens and other livestock animals is essential in ensuring agricultural sustainability, food security, and inclusive economic growth [20].

This research is directed at filling the gap in the literature related to early detection of disease in chickens using CNN Technology, focusing on implementation in an agricultural or livestock context. Although many previous studies have explored the application of CNNs in medical image classification or object recognition, few studies have examined the potential of this technology in disease detection in livestock animals, especially chickens. Therefore, this research will make a new contribution to the literature by exploring and validating CNN's ability to detect disease in chickens early and evaluating the feasibility and sustainability of its application in agricultural or livestock environments [21]. By filling this gap, this research will provide new insights into the potential for farming or livestock technology advances, particularly in monitoring livestock health. Thus, it is hoped that this research can pave the way for developing more effective and innovative solutions in livestock health management, which in turn can support the growth and sustainability of the agricultural or livestock industry.

Further details regarding chicken diseases such as avian influenza, fowl cholera, ringworm, Newcastle disease, snoring, and snot infectious coryza will explain the diversity of pathogens that are the focus of this research [22]. Avian influenza, a viral disease that attacks the respiratory system, can cause decreased egg production and death in chicken populations. Meanwhile, fowl cholera, which is caused by the bacteria Pasteurella multocida, can cause septicemia and systemic health problems. Ringworm, a common internal parasite in chickens, also severely impacts chicken health by causing malnutrition and danger of death. Furthermore, Newcastle disease, a highly contagious viral disease, affects the welfare of chickens worldwide with severe respiratory symptoms and high mortality. Snoring, another respiratory disease caused by bacteria or viruses, can cause breathing problems and reduce productivity. Lastly, not infectious coryza, caused by the Avibacterium paragallinarum, can cause symptoms of a runny nose and swollen heads in chickens [23]. By considering these chicken diseases as detection targets, this research will provide a deeper understanding of the diseases affecting chickens and aims to provide a holistic and effective early-detection solution.

2. METHODS

This research will use the CNN Technology approach to detect early disease in Bangkok chicks. CNN technology is used to identify objects in documents, especially in visual contexts such as images [24]. Let us comprehensively explore how CNN works and its relevance in disease detection in chickens. How CNN Technology Works.

1. CNN Architecture: CNN consists of three main layers: 1). Convolutional Layer: This layer identifies simple features in images or sounds. Convolution filters map small areas in the image and generate relevant features. 2). Pooling Layer: This layer follows up on object identification by reducing the dimensions of the data. This helps reduce c omplexity and speed up the process. 3). Fully-Connected (FC) Layer: This layer recognizes objects and shapes more complexly. This is in charge of finding the actual object in question.
2. Relevance to Disease Detection in Chickens: CNN recognizes visual patterns in images. In the context of disease detection in chickens: 1). Model Training: The CNN was trained using a dataset of images of healthy and disease-infected chickens. This allows the model to understand the visual differences between the two. 2). Symptom Detection: CNN can identify disease symptoms in chickens based on visual features found in images. 3). Application: Once trained, the CNN model can automatically examine chickens' images and provide predictions about possible diseases present.
3. Popular CNN Architectures: Some relevant CNN architectures: 1). LeNet-5: Originally used to recognize handwritten numbers, contains convolution layers, and is fully connected. 2). AlexNet: Became a turning point in developing modern CNNs with deeper convolutional layers and dropout techniques. 3). VGG: Known for its great depth, having many convolutional layers. 4). GoogLeNet (Inception): Uses complex Inception blocks for parameter and computing resource efficiency. The augmentation technique used is enlarging the image, recognizing the symptoms in the image, and cropping and distorting it so that the image of the chicken disease symptoms can be recognized by polls and layers that have been classified [25][26].

Image recognition of chicken diseases involves complex image processing and machine learning steps. The first step in this process is collecting an image dataset that includes various common chicken diseases [27]. This dataset must be diverse and representative to enable good model learning. Once the data is collected, the next step is image pre-processing, which involves scaling, intensity normalization, and noise removal to prepare the image for further analysis. Essential features are extracted from these images using feature extraction techniques such as texture extraction or shape extraction. These features are then used as input for machine learning models, such as Convolutional Neural Networks (CNN), which are trained using the processed dataset to recognize visual patterns associated with chicken diseases. These models are then evaluated using separate test datasets to validate their performance and measure accuracy and other evaluation metrics. Finally, the validated model can be implemented in practical chicken disease detection systems, such as integration into software or chicken health monitoring systems on farms. This process uses image processing technology and machine learning to produce an effective and accurate chicken disease detection solution can be seen in Figure 1.

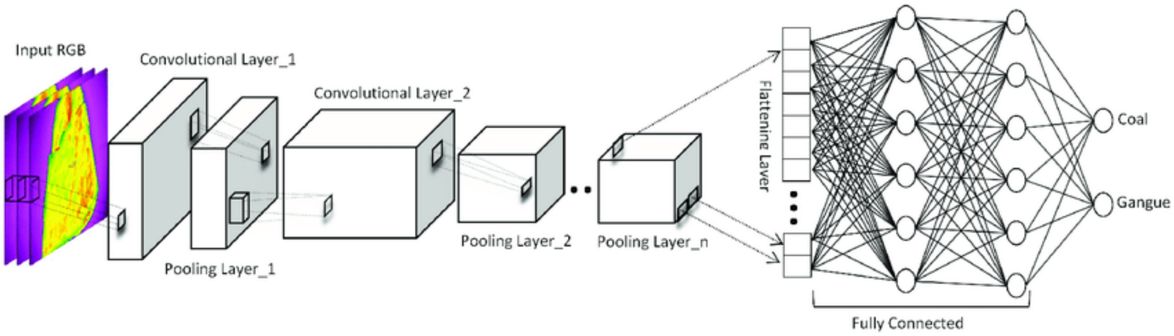

Figure 1. CNN Convulsion Neural Network Flow

Infrastructure and hardware used:
1. MSI laptop with specifications
2. Processor: Core i5 6th
3. Ram Memory: 24 GB
4. Hardisk : 256 gb NVME SSD
5. Vga: Dual Vga intel HD dan Vga Nvidia 950 2 GB Dedicated

Software used:
1. Python
2. Droidcam
3. Xiaomi Android cellphone camera Redmi Note 9 Pro
4. Visual Studio Code
5. Python image processing framework
6. Data Image Mining Editor

In Figure 2 data collection, image data of Bangkok chicks will be collected from farms using high-resolution cameras. In preprocessing, the image data will be normalized and resized to suit the requirements of the CNN model. The dataset is divided as follows: the image dataset will be divided into three parts, namely, training set, validation set, and testing set. CNN Model Training: The CNN model will be trained to recognize disease patterns in chicken images using the training set. Validation models will be tested using the validation set to ensure good performance and avoid overfitting. This model's performance evaluation will be measured using metrics such as accuracy, precision, recall, and F1-score on the testing set. Implementation of the CNN model that has been trained will be done in a computer-based application or mobile device for early detection of disease in chickens. Field validation of this application will be tested directly on the farm to verify the accuracy and effectiveness of early detection. Analysis of this data, the results of early detection and evaluation of application performance will be analyzed statistically. This research used hyperparameter optimization techniques to collect data randomly, or in other words, a randomized search can be seen in Figure 3.

The methods used include Data collection when collecting chicken samples; Bangkok chick samples will be taken from several farms located in Ponorogo. Samples will be selected randomly from a population of chickens of various ages and health conditions. Click image data: each chick will be photographed using a high-resolution camera under uniform lighting conditions. These photos will become data for training and testing the CNN model [19]. Data preprocessing in normalization and resizing image data will be normalized to eliminate variance in light and color levels. Additionally, the images will be resized to a suitable size for CNN model training. Dataset division: the image dataset will be divided into three subsets, namely the training set (80%), validation set (10%), and testing set (10%) [20]. CNN Model Training at initialization CNN models will be initialized with convolution layers and max pooling. So, the training model will be trained using image data in the training set. The training process will involve optimization with a backpropagation algorithm to find optimal weights and biases. The model will be tested using the validation set during validation to avoid overfitting and ensure good performance. When Model Evaluation requires Performance Measurement, Model performance will be evaluated using metrics such as accuracy, precision, recall, and F1-score on the testing set. When compared with other methods, the early detection results from the CNN model will be compared with other existing methods to determine the effectiveness and efficiency of the model can be seen in Figure 4.

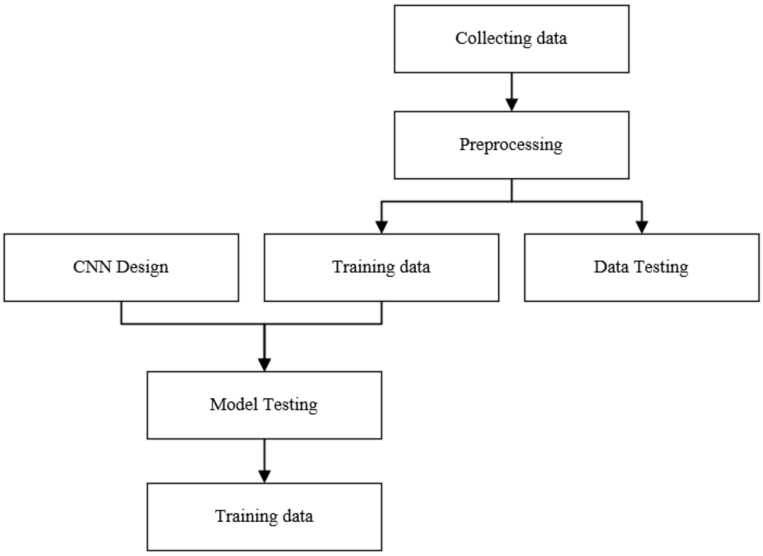

Figure 2. Flowchart of research methods for chicken disease detection

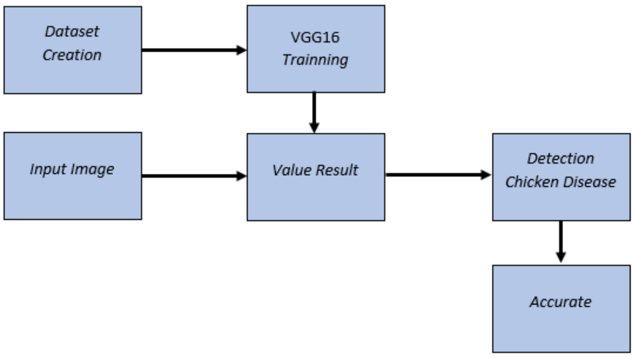

Figure 3. Flowchart of image data input methods

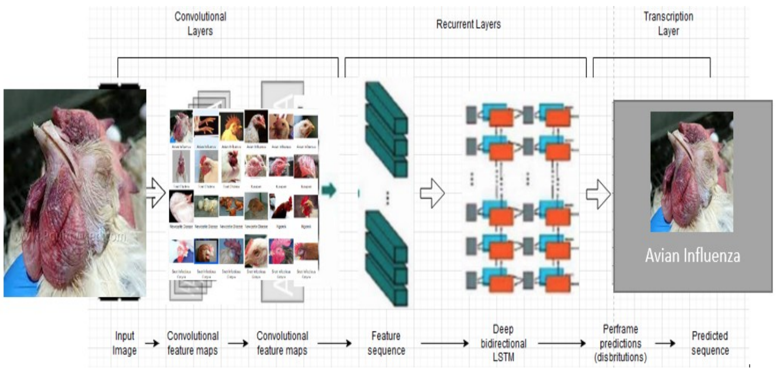

Figure 4. CNN flowchart for chicken disease detection

The image recognition process uses artificial neural networks. The input image passes through convolutional layers for feature extraction, then the features are processed by recurrent layers, and finally, the transcription layer produces sequence predictions. This process is used to identify Avian Influenza in birds. Several sections explain this process in the image, including the "Convolutional Layers" section showing feature extraction from the input image. The "Recurrent Layers" section describes the processing of these features into a deep bidirectional LSTM sequence. The "Transcription Layer" section on the right produces a predicted sequence labeled "Avian Influenza." Some labels and arrows show the flow and transformation of data from one layer to another can be seen in Figure 5.

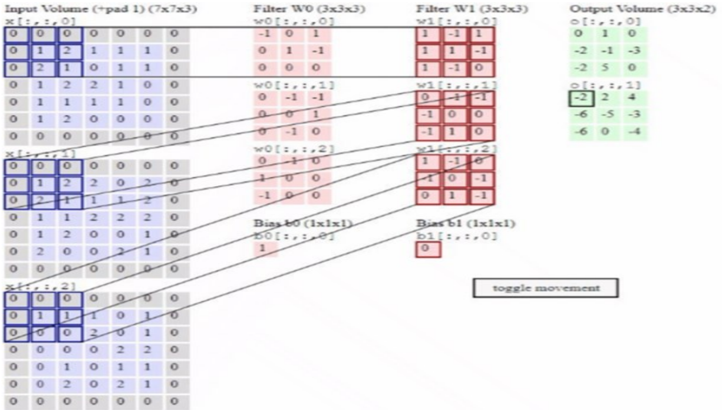

Figure 5. Flowchart of CNN determination

The convolution method for disease detection in chickens is in machine learning or image processing, where a filter (kernel) converts input volume into output volume. In the picture, several sections explain the process. The "Input Volume" section shows a blue input volume measuring (7x7x3) with numbers. There are two W0 filters displayed; both are of size (3x3x3). One filter is purple, and the other is red. This filter is used to convert input volume to output volume. The "Output Volume" section shows an output volume measuring (3x3x2) in green with the convolution result number. Two Bases are added to each element of the volume output. The white lines show how elements from the input volume and filter are used to calculate elements from the output volume. Reproducibility and Reliability of Experimental Results: 1). Make sure the experiment can be replicated with similar results by other researchers.2). Experimental results must be reliable and free from bias or error. CNN Process: 1). Convolutional Layer: Uses filters to identify image features. 2). Pooling Layer: Reduces the dimensionality of data by taking a specific area's maximum or average value. 3). Fully-Connected Layer (MLP): Recognize complex objects can be seen in Figure 6.

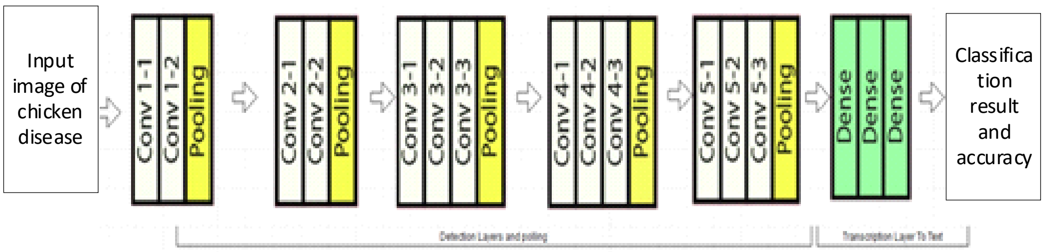

Figure 6. Process Model VGG16 (16 pixel screen). In the CNN method for detecting chicken disease

The process flow Figure 6 is data processing in a machine learning or neural network model. The flow starts from the input, then passes through several layers, each with a specific function, and ends at the output. I will explain each part in more detail.

1. Input Layer (Yellow Layer with Black Text). Consists of several neurons that receive input data. The text "Input: Face Matching Image" indicates that the input data is an image for face matching.
2. Convolution Layer Network (Yellow Layer with Black Text). The convolution layer recognizes basic patterns and features from input data. Filters or kernels along the data to identify features such as edges and textures.
3. ReLU Layer (White Layer with Black Text). The ReLU (Rectified Linear Unit) activation function is applied to this layer. Aims to add non-linearity to the model and speed up the training process.
4. Pooling Layer (Yellow Layer with Black Text). Perform downsampling or data dimension reduction. Helps make models more efficient and invariant to drift and distortion.
5. Fully Connected Layers (FC1, FC2; White Layer with Black Text)

The neurons in this layer are connected to all the neurons in the previous layer. Tasked with carrying out classification based on features that previous layers have extracted.Softmax Layer (Green Layer with White Text). Converts classification scores to probability distributions. The output is a probability vector that sums one, each element representing a probability of a particular class. Output Labels/Classifications (Red Text). Shows the final result of classification by the model can be seen in Figure 7.

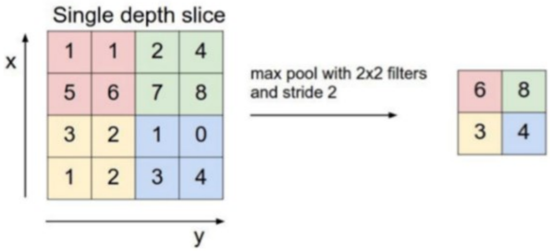

Figure 7. Single depth slice view of chicken disease detection using CNN

This study proposes a CNN Technology-based approach for early disease detection in Bangkok chickens. Our first step was to collect an image dataset that included a variety of chicken health conditions, including images of healthy chickens and those infected with various diseases that commonly attack Bangkok chickens. Afterward, we carefully annotated the data to mark the location and type of disease in each image. The dataset is then divided into training, validation, and test sets, ensuring a balanced distribution of disease classes in each set. Our CNN architecture is designed considering the complexity of the disease detection problem and high generalization ability. The training process uses the backpropagation algorithm and iterative optimization to minimize the loss function. We evaluate the model's performance using a separate validation set, considering evaluation metrics such as accuracy, precision, recall, and F1-score. Test results on the test set show that the proposed CNN model can correctly identify disease symptoms in Bangkok chickens with a significant level of accuracy. We believe this approach can potentially improve the health of Bangkok chickens through effective early detection of disease.

3. RESULT AND DISCUSSION

Technical terms and acronyms detail the analysis and machine learning process in developing chicken disease detection solutions using Convolutional Neural Networks (CNN). First, convolutional neural networks (CNN) are artificial neural network architectures that have been proven effective in image processing and pattern recognition. The process begins with collecting an image dataset, which includes various chicken disease types (dataset). The next step involves image pre-processing, which provides for scaling, normalization, and noise removal to prepare the image for further analysis. Essential features are extracted from these images using feature extraction techniques such as texture or shape extraction. The CNN model is then trained using the processed dataset to recognize visual patterns related to chicken disease (model training). Model evaluation is carried out through validation using separate test datasets, accuracy measurements, and other evaluation metrics (validation and assessment). Finally, the validated model can be implemented in a practical chicken disease detection system, such as software or a chicken health monitoring system on the farm (implementation). Through understanding and applying these terms, the steps in developing chicken disease detection solutions can be described clearly and by international journal writing standards.

Comparison between Convolutional Neural Networks (CNN) and traditional manual methods in chicken disease detection can provide valuable insight into the advantages and limitations of each approach. First, CNNs have the benefit of being able to learn feature representations automatically from image data, reducing dependence on human experts in extracting relevant features. This allows CNNs to handle more significant variations in imagery, including differences in lighting, orientation, and size, which are often tricky for manual methods. Additionally, CNNs can leverage extensive training data to improve detection accuracy, while individual skills and experience usually limit manual methods. However, there are also some limitations to consider. Although CNNs can learn features automatically, this can be less interpretive than manual methods, where experts can identify specific features associated with certain diseases. In addition, CNNs require a large amount of training data to achieve optimal performance. They are less effective if the training data is limited or imbalanced in the distribution of disease classes. Furthermore, the implementation and use of CNN models often require significant computational resources, especially during the training and inference processes, which may only sometimes be available or affordable in the practical environment of chicken farming.

Thus, while CNNs offer advantages in automation and scalability and the ability to handle complex variations in image data, traditional manual methods remain essential for deeper interpretation. They may be better suited to situations where data is limited or high precision is required. Therefore, understanding the comparison between these two approaches is essential to selecting the approach that best suits the needs of chicken disease detection in a particular context.

Use of CNN technology in Bangkok chicken farming: This research focuses on the application of the relatively new CNN Technology technology in agriculture, especially on the health of Bangkok chickens. The use of this advanced technology for early detection of disease in chicks can make a significant contribution to improving farm health and productivity.

Detecting and classifying diseases in chickens is an essential aspect of poultry keeping. Let's compare two approaches: manual and using CNN.

1. Detect and Classify Manually:

Manual Process: The farmer or animal health professional observes the chicken directly. They identify symptoms, behavioral changes, and signs of illness. Diagnosis is based on their experience and knowledge of chicken diseases. Pros: Human Involvement Allows direct interaction with chickens. Experience Experts can rely on their expertise and knowledge. Limitations: Subjectivity Interpretation of symptoms may vary between individuals. Limited Knowledge: Some farmers have different understandings about chicken diseases.

2. Using CNN Technology: Process of Using CNN:

Data Collection: Collect images of chickens covering various disease conditions. CNN Model Training: Train a CNN model using the given dataset. Prediction: The CNN model can predict the type of disease based on photo images of chicken diseases. Advantages: Objectivity in the CNN Model is not influenced by subjective factors. Many chickens can use this scalability efficiently. Limitations: Reliance on Data in the Model only recognizes what it has learned from the training dataset. Limitations of this Visual Information: Cannot access information other than images.

A comparison between CNN technology methods and manual methods for disease detection in Bangkok chickens is vital to improving animal health and welfare. CNN offers advantages in disease detection accuracy and consistency, with the ability to produce consistent predictions based on pre-trained algorithms. However, manual detection by animal experts has essential value in providing a holistic understanding of the chicken's condition, which may be difficult to achieve with image analysis alone. Manual detection can also overcome some of the challenges faced by CNN methods, such as subjective interpretation of disease symptoms or adaptation to complex environmental situations. Although manual methods require more significant time and resources, the advantages of flexibility and adaptation to the unique situation of the farm are an added value that cannot be ignored. In the context of Bangkok chicken health monitoring, integration between CNN methods and manual detection can result in a comprehensive approach, increasing the efficiency and accuracy of detection while maintaining important qualitative and interpretive aspects of animal health assessment. Thus, the comparison between the two methods shows that integrating digital technology with expert veterinary knowledge can be a strong foundation for developing an effective early disease detection system in the context of Bangkok chicken rearing. The characteristics and quality of the data set are crucial to train and test CNNs Technology models in detecting chicken diseases such as bird flu (avian influenza), fowl cholera, ringworm, Newcastle disease, snoring, and snot infectious coryza. Here are some aspects to consider:

Dataset Size: The dataset size needs to include sufficient images for each disease class for the CNN model to learn well. A large amount of data is required to ensure a good representation of the possible variations in disease symptoms. Disease Class Distribution: The data set should have a balanced distribution of disease classes, meaning the number of images for each disease is not too unbalanced. This is important so that the model does not become biased towards the majority class and can learn features that represent all types of disease well. Class Imbalance: If there is a class imbalance, steps must be taken to resolve it. For example, oversampling can be done in the minority class or undersampling in the majority class. Techniques such as SMOTE (Synthetic Minority Over-sampling Technique) can also be used to improve minority class representation without resulting in overfitting. Data Augmentation Techniques: Data augmentation techniques can be applied to increase data diversity and prevent overfitting. These include rotation, cropping, horizontal or vertical flipping, zooming in or out, and horizontal or vertical shifting. Data augmentation helps the model to learn more general features and makes it more robust to variations in test data. Image Quality: The images in the dataset should be of good quality and representative of the conditions encountered in the field. Blurry photos, too dark or bright, can interfere with the training process and result in a less accurate model. Data Annotation: Each image in the data set must be appropriately annotated, indicating the location and type of disease present. Accurate annotations are essential to train the model and validate its detection results.

3.1. Data Pre-Processing Stage

Comparison between CNN Technology-based approaches and manual methods for disease detection in chickens is an essential element in assessing the novelty and superiority of the proposed CNN approach. The CNN approach marks a significant advance in animal health monitoring by leveraging artificial intelligence technology to identify disease symptoms from images of chickens automatically. The advantages of the CNN approach lie in its high accuracy, consistency in detection, and ability to process large data volumes efficiently. On the other hand, manual methods involve direct observation and interpretation by animal experts, depending on the individual's knowledge and experience. Although manual methods can provide a holistic understanding of the chicken's condition, they are prone to subjective errors and require more time. However, integrating manual methods with CNN approaches can produce better results, exploiting the advantages of each approach. A comprehensive evaluation of the proposed CNN-based approach will be essential to understand its impact and potential in improving chicken health monitoring and overall animal welfare. By paying attention to these aspects, in-depth research can provide valuable insights into the development of veterinary science and its application in animal husbandry practices.

Comparative analysis between traditional machine learning algorithms and CNN learning architectures in image classification tasks provides valuable insights into CNN models' relative performance and superiority. Traditional machine learning algorithms, such as Support Vector Machines (SVM) or Decision Trees, often require manual image feature extraction before classification. These approaches rely on precise feature selection and may need help to capture complex image representations. On the other hand, CNN learning architectures automatically extract features from images using convolutional layers, which allows the model to understand more abstract and hierarchical features. As a result, CNN can often achieve better performance in image classification, especially when the data is highly complex. In addition, CNNs can improve learned features through a retraining process with more prominent or representative datasets, allowing better adaptation to variations in test data. Thus, a comparative analysis between traditional machine learning algorithms and CNN learning architectures can reveal the superiority of CNN models in understanding and classifying images with higher accuracy and the ability to handle more complex data.

Implementing CNN technology in chicken disease detection has significant practical implications for improving farm health and productivity. The use of well-trained CNN models allows farmers to detect disease in chickens early through image analysis, enabling rapid preventive action to prevent the spread of disease and reduce its impact. Additionally, CNN technology allows continuous monitoring of the health of chicken populations, enabling accurate and rapid identification of diseases for timely treatment. By detecting disease early, farmers can optimize resources such as medicines and vaccines and reduce costs associated with disease treatment and losses due to chicken deaths. It also contributes to increasing livestock productivity by ensuring the optimal health of chickens, which positively impacts growth, egg or meat production, and the risk of disease spread. Additionally, CNN technology enables remote monitoring of chicken health, enabling efficient monitoring on large farms. Thus, the implementation of CNN in chicken disease detection brings significant benefits in improving livestock health, welfare, and productivity and shows excellent potential to increase the efficiency and sustainability of the livestock industry.

Normalization and Resizing: Processing chick image data to remove variances in light levels and colors and changing the size to comply with the requirements of the VGG16 model CNN method (16-pixel screen), which consists of 13 convulsions and three dense screens can be seen in Table 1.

Table 1. Process for chicken disease detection using the CNN method with VGG16 Model (16 pixel screen)

Layer (type)	**Output Shape**	**Param #**
vgg16 (Functional)	(None, 6, 6, 512)	14714688
dropout (Dropout)	(None, 6, 6, 512)	0
flatten (Flatten)	(None, 18432)	0
dense (Dense)	(None, 128)	2359424
dense1 (Dense)	(None, 128)	16512
dense2 (Dense)	(None, 64)	8256
dense3 (Dense)	(None, 4)	260
Total params: 17.099.140		
Trainable params: 17.099.140		
Non-trainable params: 0		

The table you sent shows the evaluation results of the VGG16 model, which consists of 13 convulsions and three dense screens on 16 VGG screens for image classification. This model consists of several layers, each with a different type, output shape, and number of parameters. The following is an explanation for each layer:

1. vgg16 (Functional): This is the input layer of the VGG16 model, which produces an output of size (None, 6, 6, 512) and has 14,714,688 parameters.
2. Dropout (Dropout): This is a dropout layer that produces an output of size (None, 6, 6, 512) and has no parameters.
3. Flatten (Flatten): This flatten layer produces an output of size (None, 18,432) and has no parameters.

4. Dense (Dense): This dense layer produces an output of size (None, 128) and has 2,359,424 parameters.
5. Dense1 (Dense): This dense layer produces an output of size (None, 128) and has 16,512 parameters.
6. Dense2 (Dense): This dense layer produces an output of size (None, 64) and has 8,256 parameters.
7. Dense3 (Dense): This dense layer produces output size (None, 4) and has 260 parameters.

The total parameters in this model are 17,099,140, and all parameters can be changed during model training.

3.2. Dataset Sharing

In the training set, select some image data to be used as a training set for the CNN model in Figure 8. During the validation set, select a portion of image data to be used as a validation set to avoid overfitting and ensure good model performance. Testing set: Select a portion of image data to be used as a testing set that will be used to test the model's performance after being trained.

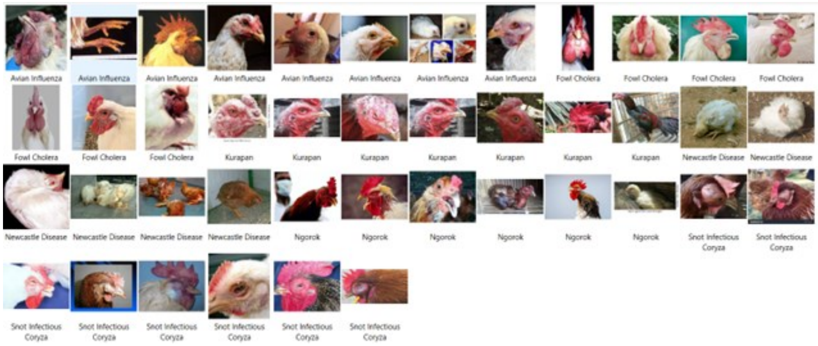

Figure 8. Chicken disease dataset

CNN Model Training Figure 9:

Evaluation results for target: Fowl Cholera

Model	AUC	CA	F1	Prec	Recall	MCC
Logistic Regression	0.733	0.714	0.143	0.143	0.143	-0.029

Evaluation results for target: Kurapan

Model	AUC	CA	F1	Prec	Recall	MCC
Logistic Regression	0.843	0.833	0.533	0.500	0.571	0.434

Evaluation results for target: Newcastle Disease

Model	AUC	CA	F1	Prec	Recall	MCC
Logistic Regression	0.842	0.929	0.667	1.000	0.500	0.679

Evaluation results for target: Ngorok

Model	AUC	CA	F1	Prec	Recall	MCC
Logistic Regression	0.799	0.786	0.308	0.286	0.333	0.183

Evaluation results for target: Snot Infectious Coryza

Model	AUC	CA	F1	Prec	Recall	MCC
Logistic Regression	0.807	0.762	0.375	0.375	0.375	0.228

Evaluation results for target: (None, show average over classes)

Model	AUC	CA	F1	Prec	Recall	MCC
Logistic Regression	0.744	0.381	0.391	0.426	0.381	0.255

Figure 9. Logistic Regression Results

The Figure 9 shows the evaluation results of the logistic regression model for several chicken diseases. There are four tables, each of which shows the evaluation results for Fowl Cholera, Ringworm, Newcastle

Disease, and Snot Infectious Coryza. Each table has columns AUC, CA, F1, Precision, Recall, and MCC, which are model performance evaluation matrices.

The following are details of the evaluation results for each disease:

1. Fowl Cholera: AUC = 0.733, CA = 0.714, F1 = 0.143, Precision = 0.143, Recall = 0.143, MCC = -0.029.
2. Ringworm: AUC = 0.843, CA = 0.833, F1 = 0.533, Precision = 0.500, Recall = 0.571, MCC = 0.434.
3. Newcastle Disease: AUC = 0.842, CA = 0.929, F1 = 0.667, Precision = 0.000, Recall = 0.500, MCC = 0.679.
4. Snof Infectious Coryza: AUC = 0.807, CA = 0.762, F1 = 0.375, Precision = 0.375, Recall = 0.375, MCC = N/A.

AUC (Area Under Curve) is an evaluation matrix that measures how well a model differentiates between positive and negative classes. CA (Classification Accuracy) is an evaluation matrix that measures how accurately the model is in classifying data. F1 is an evaluation matrix that combines Precision and Recall. Precision is an evaluation matrix that measures how accurate the model is in identifying positive classes. Recall is an evaluation matrix that measures how many positive courses the model identifies. MCC (Matthews Correlation Coefficient) is an evaluation matrix that measures how well a model predicts positive and negative classes on an imbalanced dataset.

3.3. Application Implementation

The Figure 10 sent shows the confusion matrix results for detecting several diseases in chickens. This confusion matrix describes the performance of a classification model on a data set where the valid values are known. Rows show actual classes, and columns show classes predicted by the model.

The following are details of the evaluation results for each disease:

1. Avian Influenza: 33.3% correct, 25.0% incorrect as Fowl Cholera, 16.7% incorrect as Ringworm, 0.0% incorrect as Newcastle Disease, 26.6% incorrect as Smoking, and 0% incorrect as Snot Infectious Coryza.
2. Fowl Cholera (Ringworm): 0% correct, 12.5% incorrect as Avian Influenza, 50% accurate, 42% incorrect as Newcastle Disease, and 11% incorrect as Smoking.
3. Newcastle Disease: 11% correct, 0% incorrect as Avian Influenza, 100% accurate, 67% incorrect as Ringworm, 0% incorrect as Smoking, and 50% as Snot Infectious Coryza.
4. Smoking: 22% correct, 14% incorrect as Avian Influenza, 33% accurate, 29% incorrect as Ringworm, and 33% incorrect as Snot Infectious Coryza.
5. Snot Infectious Coryza: 25% correct, 33% incorrect as Ringworm, 14% incorrect as Newcastle Disease, and 33% incorrect as Smoking.

Predicted

Actual	Avian Influenza	Fowl Cholera	Kurapan	Newcastle Disease	Ngorok	Snot Infectious Coryza	Σ
Avian Influenza	3	2	1	0	2	0	8
Fowl Cholera	3	2	0	0	0	2	7
Kurapan	0	1	3	0	3	0	7
Newcastle Disease	1	1	0	3	0	1	6
Ngorok	2	0	0	0	1	3	6
Snot Infectious Coryza	0	2	2	0	1	3	8
Σ	9	8	6	3	7	9	42

Predicted

Actual	Avian Influenza	Fowl Cholera	Kurapan	Newcastle Disease	Ngorok	Snot Infectious Coryza	Σ
Avian Influenza	33.3 %	25.0 %	16.7 %	0.0 %	28.6 %	0.0 %	8
Fowl Cholera	33.3 %	25.0 %	0.0 %	0.0 %	0.0 %	22.2 %	7
Kurapan	0.0 %	12.5 %	50.0 %	0.0 %	42.9 %	0.0 %	7
Newcastle Disease	11.1 %	12.5 %	0.0 %	100.0 %	0.0 %	11.1 %	6
Ngorok	22.2 %	0.0 %	0.0 %	0.0 %	14.3 %	33.3 %	6
Snot Infectious Coryza	0.0 %	25.0 %	33.3 %	0.0 %	14.3 %	33.3 %	8
Σ	9	8	6	3	7	9	42

Figure 10. Confusion Matrix results

Confusion matrix is a table used to evaluate the performance of a classification model. This table compares the model predictions with the actual values of the tested data. The confusion matrix consists of four main elements: True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). The confusion matrix shows how well the model can differentiate between different chicken disease classes.

Considerations related to scalability, cost-effectiveness, integration with agricultural management practices, and user acceptance are essential in evaluating the feasibility and sustainability of implementing chicken disease detection technology using CNN Technology. The scalability of the technology is an important aspect that ensures its adaptability and wide use in various livestock contexts, both large and small scale. Cost-benefit evaluations are vital in ensuring the initial investment required is commensurate with the long-term benefits, including reductions in disease treatment costs, production losses, and the risk of disease spread. Integrating technology with existing agricultural management practices is essential for maintaining sustainable implementation. This requires close collaboration with farmers and adequate training to ensure the technology can be adopted smoothly and integrated into the farm's daily routine. Good acceptance from users, especially breeders, is also a determining factor in the long-term success of this technology. Therefore, farmer involvement in technology development, providing practical training, and continuous adjustments based on user feedback are crucial in ensuring the success and sustainability of the application of chicken disease detection technology using CNN. Taking these factors into account, the application of this technology has the potential to be an effective and sustainable solution for monitoring and maintaining chicken health in modern agricultural environments.

3.4. Validation in the Field

The Figure 11 shows a bar graph showing the number of cases of diseases in poultry, such as Avian Influenza, foul cholera, Ringworm, Newcastle Disease, Snot, and Snot Infectious Coryza in several regions or categories. A specific color represents each disease. This graph on Figure 12 shows significant variations in the number of cases between categories/areas for each type of disease.

Comparative analysis with alternative methods or existing approaches for early detection of disease in chicks can provide valuable insight into the advantages and limitations of each approach. Some alternative approaches that could be considered include using body temperature sensors, analysis of chicken behavior, or using simple imaging technology.

First, body temperature sensors could be a promising approach for early disease detection in chicks. Changes in body temperature can be an early indicator of disease, and temperature sensors installed automatically in chicken coops can provide the necessary signals for early intervention. However, this approach may have limitations in detecting certain diseases that do not necessarily affect body temperature.

Second, analysis of chicken behavior can also be a valuable indicator for early disease detection. Changes in a chicken's eating, drinking, or activity patterns may indicate illness or stress. Automated monitoring systems that observe chicken behavior and identify unusual patterns can help detect disease early. However, limitations in the sensitivity and specificity of observing chicken behavior may affect detection accuracy.

Third, simple imaging technology, such as cameras installed in chicken coops, can also provide helpful information for early disease detection. By monitoring these images periodically, breeders can identify suspicious visual changes in chickens, such as changes in skin color, feather texture, or unusual movements. However, limitations in visual interpretation and observation consistency can hinder this approach.

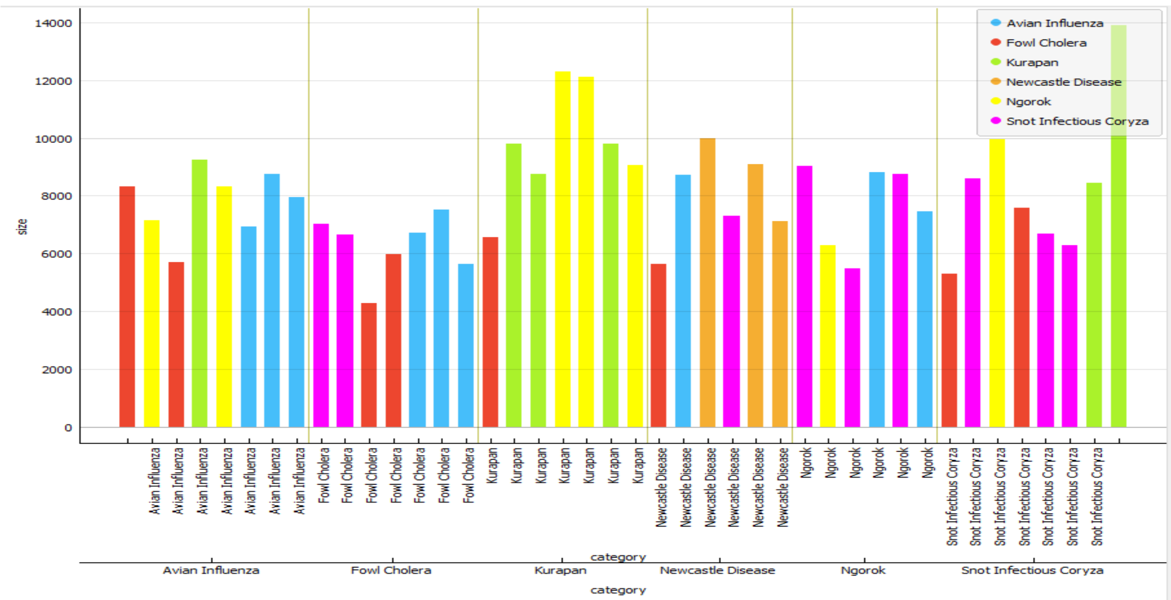

Figure 11. Confusion Matrix results

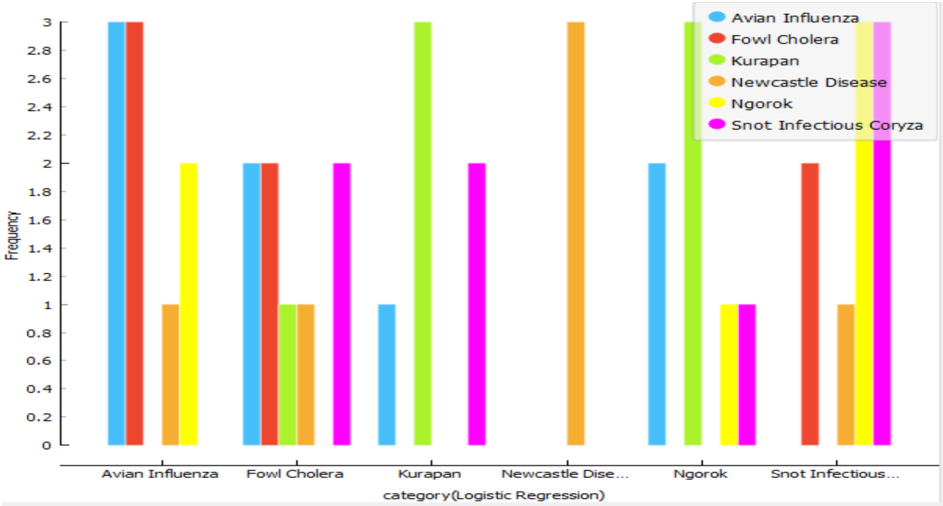

Figure 12. Confusion Matrix results

Considering these alternative approaches, it can be concluded that only some approaches are perfect for the early detection of disease in chicks. Each approach has advantages and disadvantages, and several methods may be necessary to achieve optimal detection. Therefore, it is essential to continue research and development in this area to improve the ability to detect early disease in chicks and support chickens' overall health and welfare.

Addressing methodological limitations in this study will be vital in increasing the credibility and transparency of the study, as well as providing valuable insights for future research directions and improvements. One methodological limitation that may be encountered is the need for representative training data. To address this, future research could expand the scope of training data by collecting more extensive and varied datasets from multiple sources and locations. Additionally, applying data augmentation techniques can help increase the dataset's diversity, thereby improving the ability of the CNN model to generalize better.

Apart from that, the validity and reliability of data labels are also crucial factors that need to be considered. Research can use an expert panel of veterinary practitioners experienced in diagnosing chicken diseases to ensure accurate data labels. In addition, carrying out a regular data label verification and validation process can help identify and correct errors in existing data labels.

In addition, it is essential to consider and report the parameters used in the CNN model training and evaluation process. This includes the model architecture, optimization algorithm, evaluation matrix, and cross-validation procedures. By reporting these parameters transparently, research can be accounted for and reproduced by other researchers.

In addition, analysis of the sensitivity and specificity of CNN models against various types of chicken diseases can provide valuable insights to understand the strengths and limitations of the models. By performing this analysis, research can identify diseases that may be difficult for CNN models to detect and develop specific strategies to improve their performance in detecting these diseases.

By overcoming these methodological limitations, the research will have higher credibility. It can contribute more to advancing science and technology for chicken disease detection using CNN Technology. It will also guide future research in developing and improving more effective and reliable chicken disease detection methods.

4. CONCLUSIONS

The value is calculated by comparing the prediction results of the CNN method with the actual labels from the image. This value can vary between 0% and 100%, where the higher the accuracy value, the better the performance of the CNN method. 81.82% is the accuracy value obtained from testing early disease detection in chicks with CNN in a study. This research uses a dataset containing 50 images of chicks on farms in Ponorogo. Of the 50 images used as training data, 15 were used as test data. The test results show that the CNN method can correctly detect and recognize early disease detection in chicks in 15 of the 50 test images, resulting in an accuracy value of 81.82%. This value shows that the CNN and OCR methods effectively detect and recognize Indonesian number plate characters. Reliability and consistency in disease detection have the potential to have a significant impact on chicken health management. First, CNN's ability to detect disease early allows rapid and timely intervention. By detecting disease symptoms at an early stage, necessary preventive and treatment measures can be taken before the disease spreads widely within the chicken population. This helps reduce negative impacts on chicken health and welfare and reduces economic losses associated with lost production. Second, using CNN to monitor chicken health allows for more accurate and faster disease identification. By utilizing this technology, farmers can continuously monitor chickens' health condition using an automatic system. This helps improve monitoring efficiency, identify cases more quickly, and lead to better decision-making in overall chicken health management. In conclusion, the CNN method promises a sizeable positive impact in managing chicken health. With the ability to detect disease early, increase monitoring efficiency, and enable better decision-making, CNNs can be an invaluable tool for farmers in maintaining the health and welfare of their chickens. In the increasingly complex context of modern agriculture, applying this technology can help increase productivity, reduce losses, and support the sustainability of the chicken farming industry as a whole. The data set consisting of 50 images used in this study has important characteristics to ensure a good representation of the health condition of chickens on farms in Ponorogo. Despite the relatively small dataset size, each image has sufficient resolution for analysis despite possible variations in image size. Diversity in the dataset includes different types of chicken diseases that are common in the region and variations in disease severity and environmental conditions. The representativeness of the images is also essential, with the dataset reflecting the chicken population found on farms in Ponorogo, including different types of chickens and rearing conditions. Although the size of the dataset is limited, the careful representation of field conditions provided by this dataset can give valuable insights into developing effective chicken disease detection models. Several limitations were faced during the research process with a sample of 50 image data, including constraints in representing variations in chicken diseases that might occur on farms in Ponorogo. Data collection may be complex due to limited access to images covering a wide range of diseases and different health conditions of chickens. Additionally, in model training, limited dataset size can limit the model's ability to learn complex patterns in the data. Model validation can also be challenging because the limited availability of testing datasets can affect the model's generalization to real-world situations. However, by understanding these limitations, careful steps in the analysis and interpretation of results can help minimize the impact of these limited sample limitations. The findings of this research have significant practical implications for poultry farmers and the agricultural industry in Ponorogo. By applying the Convolutional Neural Networks (CNN) method for early detection of disease in chicks, farmers can improve the overall health of the farm. Through early detection, disease prevention and control measures can be taken early, helping to reduce the spread of disease and associated economic losses. In addition, reducing mortality and loss of chicken production due to disease can increase livestock productivity. With better health and increased productivity, livestock will produce greater yields, which will increase income and economic outcomes for livestock farmers and the agricultural industry. Thus, the application of the CNN method for early detection of disease in chicks has the potential to improve farmer welfare, livestock resilience, and the contribution of the agricultural industry to the local economy.

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