Classification-based CNNs of Thai Native Chickens

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Abstract

This paper presents the use of deep learning network-based Convolutional Neural Networks (CNNs) to enhance the efficiency of classifying purebred Thai native chickens for conservation purposes. This study specifically focuses on Thai native chicken species known as Leung Hang Khao. Due to the significant genetic diversity of the Thai native chickens, it typically requires experts to accurately identify the breeds. There are four groups of the Thai native chickens that were considered in this work; namely, purebred Leung Hang Khao male, purebred Leung Hang Khao female, crossbred male, and crossbred female. A total of 1,000 images have been collected, in which 250 images are from each group. Then, the data is divided into three sets which are training set, validation set, and testing set, in the ratios of 60:20:20, 70:20:10, and 80:10:10, respectively. Four architectures of the CNNs have been employed for verification, i.e., LeNet-5, CNN1, CNN2, and CNN3, with epochs set at 10, 20, and 50 epochs for each architecture. The results show that the CNN1 architecture with an 80:10:10 ratio and 10 epochs yielded the highest accuracy in learning, validation, testing, and prediction. Moreover, it required relatively less testing time with predicted accurate results of 100 %. The obtained results demonstrate that using the deep learning network-based convolutional neural network with a simple architecture setting can effectively classify Thai native chicken breeds.

Keywords: Deep Learning Models; Classification; Convolutional Neural Networks; Thai Native Chickens; Leung Hang Khao

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Introduction

Thai native chickens (*Gallus gallus domesticus*) are indigenous to South and Southeast Asia, including India, southern China, Myanmar, Vietnam, and Thailand (Liu et al., 2006). Descended from the red junglefowl (*Gallus gallus*), these chickens have been raised by Thai farmers for centuries (Fumihito et al., 1994; Sawai et al., 2010; Dorji et al., 2012; Mekchay et al., 2014). They are renowned for their disease resistance and adaptability to local climates, showing significant genetic diversity. Despite this diversity, the Department of Livestock Development in Thailand has officially recognized only four native breeds: Pradu Hang Dam, Leung Hang Khao, Dang, and Chee (Mekchay et al., 2014). Surveys across various Thai provinces indicate that the Pradu Hang Dam and Leung Hang Khao breeds are the most commonly raised. These chickens are vital to rural communities, providing an affordable source of protein and supporting both primary and secondary livelihoods. In addition to being raised for consumption, they are also valued for ornamental purposes and participation in fighting competitions. Fighting chickens, particularly the Leung Hang Khao breed, were registered as a national cultural heritage in 2014, symbolizing the cultural and intellectual heritage of Phitsanulok province and Thailand. The Leung Hang Khao breed, developed specifically for combat, is known as King Naresuan's fighting rooster (Laenoi et al., 2015).

The Leung Hang Khao chicken, considered a valuable natural resource, exhibits a variety of feather colors in males, including bright dark yellow, medium yellow, light yellow (safflower or turmeric yellow), normal yellow, and ruby yellow. Their shank colors range from yellow to yellowish-black or yellowish-brown-black. This breed diversity reflects the genetic variability inherent in Thai native chickens (Katano et al., 2011). Farmers raise native chickens for various purposes, such as consumption, sale, and sport, contributing to the diversity of their physical characteristics. The practice of raising different breeds together has led to both inbreeding and crossbreeding, resulting in a mix of purebred and crossbred chickens. The Department of Livestock Development, Thailand, classifies these chickens based on physical characteristics such as feather color, beak, comb, shanks, and body shape. However, some chickens cannot be clearly classified and are grouped by male feather color into categories such as Leung, Pradu, Khiao, Dang, Chee, Thao, Dang/Lai, and Sa (Laenoi et al., 2015; Khumpeerawat et al., 2021; Wiyabot and Kiattinarueyut, 2022; Yaemkong et al., 2024).

Among native chicken breeds, Pradu Hang Dam and Leung Hang Khao are the most popular, followed by other breeds like Thao Hang Khao, Lai Hang Khao, Nok Dang Hang Dang, Khiao Hang Dam, Thao Hang Dam, Thong Dang Hang Dam, Nokgod Hang Dam, Khiao Lao Hang Khao, and Pradu Lao Hang Khao (Pramual et al., 2013; Mekchay et al., 2014; Phasouk et al., 2021). The Leung Hang Khao breed, in particular, is noted for its feather color diversity (Figure 1 and 2). Surveys in Phitsanulok province revealed that no Leung Hang Khao chickens fully met the standard perfection characteristics (beautiful face, color, shapes, shanks, and demeanor) (Yeamkong et al., 2021; Siriwadee et al., 2023). Efforts are being made to preserve purebred native chickens, with annual competitions organized to showcase these breeds. However, selecting purebred native chickens is challenging and requires significant expertise. In a case study in (Mekchay et al., 2014; Hata et al., 2021), discrepancies were observed in scoring native chickens based on standard perfection characteristics, particularly in color-related traits such as eye color, beak color, shank color, and feather color. This highlights the difficulty in correctly identifying native chicken breeds by visual inspection, especially for those lacking sufficient experience and expertise.


(a) Individual 1


(b) Individual 2

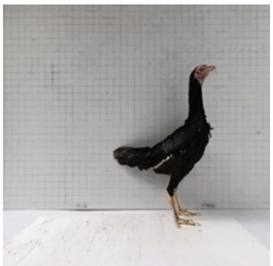

(c) Individual 3


(d) Individual 4


(e) Individual 5

Figure 1 Samples illustrating the diversity of male Thai native chickens (Leung Hang Khao).


(a) Individual 1


(b) Individual 2


(c) Individual 3


(d) Individual 4

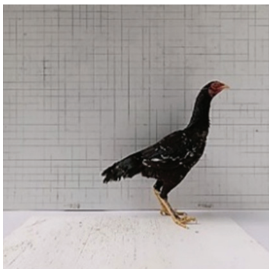

(e) Individual 5

Figure 2 Samples illustrating the diversity of female Thai native chickens (Leung Hang Khao).

Despite the significance of these breeds, surveys in Phitsanulok Province have yet to identify Leung Hang Khao chickens that fully meet breed standards for both males and females. The development breeds of chickens for fighting competitions have contributed to the current diversity of Thai native chickens, with the introduction of foreign breeds from countries such as Burma and Vietnam. These imported breeds, characterized by distinct comb shapes, feather colors, beak colors, and shank colors, have been bred with Thai native chickens to enhance their fighting abilities (Laenoi et al., 2015; Thinh et al., 2015; Rotimi et al., 2016; Buranawit et al., 2016). This genetic diversity has prompted efforts by various organizations to conserve purebred Thai native chickens for future generations, including the organization of annual native chicken competitions. Accurately selecting and classifying purebred native chickens requires significant expertise in phenotype analysis. Currently, genetic markers are used to identify gene patterns in conjunction with genetic assessments for breed verification. However, this method is both costly and time-consuming (Vanhala et al., 1998; Okumura et al., 2006; Katano et al., 2011; Shimogiri et al., 2012; Dorji and Sunar, 2014; Siriwadee et al., 2023). To address these challenges, deep learning networks-based classification methods are relatively suitable for improvement of the accuracy and efficiency of breed classification in a shorter time frame, owing current technological advancement.

Currently, one of the most important technologies is the Artificial Intelligence (AI), which involves the development of machines to be intelligent, capable of recognizing, distinguishing, and processing images, sounds, and text through a computing brain that mimics the neural network system of the human brain. The machine's computing brain is powered by machine learning, which works by learning from input-output data and applying that knowledge to analyze, predict, or drive various functions for AI. Deep learning is a sub-field of machine learning that shares the same goal but employs a learning technique characterized by an Artificial Neural Network (ANN) with multiple layers, known as a Deep Neural Network (DNN) (Samek et al., 2016). In 1998, the authors in Lecun et al. (1998) introduced a neural network with a convolutional operation by increasing the number of hidden layers in a 5-layer architectural structure called LeNet-5. This architecture enhances the efficiency of calculating image features, and this technique is also known as Convolutional Neural Networks (CNNs). The working principle involves a feature extraction process, which isolates the distinct characteristics of objects in images, such as edges, curves, and slopes. These features are then input into the neural network for classification to determine what the output image represents (Kittichai et al., 2021; Ren et al., 2022).

In recent years, machine learning algorithms have found successful applications in agriculture, particularly in animal science. For example, in (Xu et al., 2024), A multi-scale feature fusion network for Amur tiger re-identification has been developed, effectively combining global and local features to enhance accuracy without the need for prior knowledge or complex annotations. However, this model may exhibit suboptimal performance on datasets of upright animals due to its feature segmentation approach, specifically designed for large quadruped mammals like tigers. Similarly, an automated system utilizing CNNs has been proposed in (Schork et al., 2024) for monitoring and analyzing dogs' sleeping patterns, achieving an 89 % similarity to manual observations, but this system is limited by variations in image quality and environmental conditions, which can impact accuracy. Likewise, deep-learning models have been evaluated for identifying laying hens' behaviors using YOLO algorithms, showing high accuracy in detecting hens on the floor, but encountering difficulties in accurately classifying dust-bathing behaviors due to the inherent complexity of this activity (Sozzi et al., 2023). Another study introduces a deep learning model, KI-CLIP, aimed at monitoring endangered wildlife with limited data. While the model achieves high accuracy through the integration of expert knowledge, it may face challenges in real-time adaptability and managing highly diverse environmental conditions (Mou et al., 2023). Furthermore, the work in (Zhang et al., 2023) presents the UA-MHFF-DeepLabv3+ model, a novel interactive segmentation approach that significantly reduces annotation time for dairy goat images, offering a fivefold improvement in speed over existing tools like Labelme. Nonetheless, the model still requires more than four clicks to achieve ideal segmentation accuracy, suggesting that further enhancements are necessary.

Likewise, for research related to the application of CNN techniques in animal science, the following studies are notable Villa et al. (2017) used CNNs to classify wildlife. The authors in Hansen et al. (2018) utilized CNNs for pig face recognition. Yao et al. (2020) employed YOLOv3 for object detection to differentiate between male and female chickens from flock images and individual chicken images, then trained the data with CNNs. This method can be practically applied for gender classification of chickens to calculate the appropriate sex ratio in free-range farming. The authors in Wang et al. (2020) used the LeNet-5 architecture for pig face recognition. Khan et al. (2020) applied deep CNNs with Rectified Linear Units (ReLU) activation functions to classify animal faces. In 2020, CNNs were used to classify images of birds in the wild by Singh et al. The authors in Raj et al. (2020) modified the VGGNet architecture for bird species classification. Transfer learning techniques were employed by comparing with the architectures of VGG16, ResNet50, MobileNet, XceptionNet, and an 8-layer CNN to classify chicken droppings for disease diagnosis, finding that XceptionNet had the highest validation accuracy at 94 % (Mbelwa et al., 2021). These studies demonstrate that deep learning techniques-based CNNs continue to be researched and developed to achieve the most efficient techniques for practical applications tailored to different animal species.

From the review of related literature, no information was found regarding the use of CNN techniques for classifying Thai native chickens. Therefore, this paper proposes using this technique to classify images of Thai native chickens between purebreds and crossbreds, starting with the Leung Hang Khao breed, which is genetically diverse in plumage color and is commonly raised throughout all regions of Thailand. The objective of this study is to develop an appropriate architecture for Thai native chicken images to enhance the efficiency of selecting purebred native chickens for conservation purposes. The LeNet-5 architecture, along with three architectures derived from LeNet-5, namely CNN1, CNN2, and CNN3, will be adopted. The data obtained from this study will serve as preliminary information for further studies on the classification of other native chicken breeds, aiming to develop tools for classifying native chickens in the future. This research could provide valuable insights for the livestock industry, especially in Thailand.

The major contributions of this work can be summarized as follows:

1. To best of our knowledge, there are no studies that have applied CNN-based methods to classify Thai native chicken breeds, especially Leung Hang Khao. This work introduced four CNN structures to classify Leung Hang Khao so that the identified results of Leung Hang Khao chickens can fully meet breed standards for both males and females, leading to no bias in annual Thai native competitions.

2. The image dataset of Leung Hang Khao chickens was collected from two real field sites. The dataset includes purebred Leung Hang Khao chickens from the first site and crossbred chickens between Leung Hang Khao and Pradu Hang Dam breeds from the second site. A total of 200 chickens

(100 males and 100 females), all aged 20 weeks or older, were selected, with 50 chickens from each breed and gender. Images were captured using an OPPO Reno3 Pro smartphone.

The remainder of the paper is organized as follows. Section II describes a theoretical background of CNNs-based approach. Section III presents the methodology of the study. The obtained results and discussion are given in Section IV. Finally, Section V concludes the paper.

Theoretical Background of CNN-Based Deep Learning

Convolutional Neural Networks (CNNs) represent a specialized architecture in deep learning, designed to handle grid-like data structures, such as images. CNNs are distinguished by their ability to learn spatial hierarchies of features through a series of operations including convolution, pooling, and fully connected layers. These operations are underpinned by specific mathematical expressions that govern the behavior and performance of the network.

1. Convolution Operation

The core operation in a CNN is the convolution, which is mathematically defined as the sum of the element-wise multiplication of a filter or kernel K with the input matrix X. For a given input image X of dimensions $H \times W \times C$ (where H is the height, W is the width, and C is the number of channels), and a filter of K dimensions $k_h \times k_w \times C$ (where k_h and k_w are the filter's height and width), the convolution operation to produce the output feature map Y is expressed by, (Equation (1))

$$Y(i,j) = \sum_{c=1}^{C} \sum_{m=1}^{k_h} \sum_{n=1}^{k_w} X(i+m-1, j+n-1, c)\, K(m,n,c) \quad (1)$$

where i and j iterate over the spatial dimensions of output feature map Y. This operation is typically followed by the application of a non-linear activation function, such as the ReLU.

2. Activation Function

The ReLU activation function introduces non-linearity into the network, which is crucial for learning complex patterns. The ReLU is mathematically defined as, (Equation (2))

$$ReLU(z) = max(0,z) \quad (2)$$

where z is the input to the activation function. ReLU is applied element-wise to output of the convolutional layer, enabling the network to learn non-linear representations of the input data.

3. Pooling Operation

Pooling layer, such as max pooling, are used to reduce the spatial dimensions of the feature maps, thereby lowering the computational complexity and making the network invariant to small translations in the input. For a feature map Y of demensions $H' \times W' \times C'$, the max pooling operation with a filter size $p_h \times p_w$ can be expressed as, (Equation (3))

$$Z(i,j,c) = \max_{m=1,\ldots p_h; n=1,\ldots p_w} Y(p_h i + m - 1, p_w j + n - 1, c) \quad (3)$$

where Z is the down sampled output feature map, and c indexes overt the channels.

4. Flattening and Fully Connected Layers

After the convolutional and pooling layers, the multidimensional output feature maps are flattened into a one-dimensional vector f, which is then passed through fully connected layers. If w represents the weight and b represents the biased for a fully connected layer, the output o is given by, (Equation (4))

$$o = w^T f + b \tag{4}$$

In the context of classification tasks, the output from the fully connected layer is typically passed through a softmax function to produce a probability distribution over the target classes.

5. Softmax Function

The softmax function is used in the output layer of a CNN when the task is to classify the input into one of several categories. Given a vector of raw scores $o = [0_1, 0_2, \ldots 0_W]$ where N is the number of classes, the softmax function computes the probability $P(y = i)$ that the input belongs to class i as, (Equation (5))

$$P(y = i) = \frac{exp(o_i)}{\sum_{k=1}^{N} exp(o_k)} \tag{5}$$

This function ensures that the output probabilities sum to one, allowing for a probabilistic interpretation of the model's predictions.

6. Loss Function and Backpropagation

Training a CNN involves minimizing a loss function that measures the discrepancy between the predicted output and the true labels. For classification tasks, the cross-entropy loss is commonly used, which is defined as,

$$L = -\sum_{i=1}^{N} y_i \log P(y = 1) \tag{6}$$

The loss function defined in Equation (6) represents the cross-entropy loss, which is fundamental to the training process of the CNN models used in this study for classifying Thai native chickens. It measures the discrepancy between the predicted class probabilities and the true labels, enabling the network to adjust its parameters through backpropagation and gradient descent. By minimizing this loss, the CNN learns to improve its classification accuracy across the four chicken categories: purebred male, purebred female, crossbred male, and crossbred female. The effectiveness of this loss function is reflected in the study's results, where the CNN1 model, trained with this function, achieved 100 % accuracy, demonstrating the model's ability to distinguish subtle visual differences in chicken breeds.

where y_i is true label (represented as a one-hot encoded vector) and $P(y = i)$ is the predicted probability for class i. The parameters of the network (i.e., the weights and biases) are updated using the gradient descent algorithm, which relies on the backpropagation method to compute the gradients of the loss function w.r.t. the network's parameters as, (Equation (7))

$$\theta \leftarrow \theta - \eta \frac{\partial L}{\partial \theta} \tag{7}$$

where θ represents the parameters, and η is the learning rate.

7. Convolutional Hierarchies and Feature Learning

CNNs exploit the hierarchical nature of images by stacking multiple convolutional layers. Early layers typically capture low-level features such as edges and textures, while deeper layers typically capture more abstract features such as shapes and objects. This hierarchical feature extraction is a key advantage of CNNs over traditional methods, as it allows the network to automatically learn relevant features from the data, leading to improved performance in complex visual tasks.

8. Regularization Techniques

To prevent overfitting, various regularization techniques are applied in CNNs, such as dropout, where randomly selected neurons are ignored during training. Dropout can be expressed mathematically as, (Equation (8))

$$f^{(l)} = r^{l} \odot h^{l} \tag{8}$$

where r^{l} is a binary mask vector (with each element drawn from a Bernoulli distribution), is h^{l} the output of the l-th layer, and $\odot$ denotes element-wise multiplication

9. Accuracy

Accuracy is a commonly used performance metric to evaluate the effectiveness of a Convolutional Neural Network (CNN), especially in classification tasks. It represents the proportion of correctly classified samples out of the total number of samples evaluated. The accuracy can be calculated using the following formula (Equation (9)):

$$accuracy = \frac{TP \times TN}{TP + TN + FP + FN} \times 100 \tag{9}$$

Explanation:

TP (True Positives): The number of samples that are correctly predicted as positive.

TN (True Negatives): The number of samples that are correctly predicted as negative.

FP (False Positives): The number of negative samples that are incorrectly predicted as positive.

FN (False Negatives): The number of positive samples that are incorrectly predicted as negative.

The mathematical foundation of CNNs enables the automatic learning of spatial hierarchies in data, which is critical for tasks involving complex and high-dimensional inputs such as images. Through the combined use of convolution, pooling, and fully connected layers, CNNs are able to efficiently process and classify visual information, making them indispensable in modern deep learning applications. The structure of a CNN is divided into layers, which consist of the input layer, hidden layers, and the output layer. The number of units or nodes in the output layer depends on the number of categories (classes) in the image dataset, as shown in Figure 3. If the probability value is highest for a particular category, that category is considered the predicted answer.

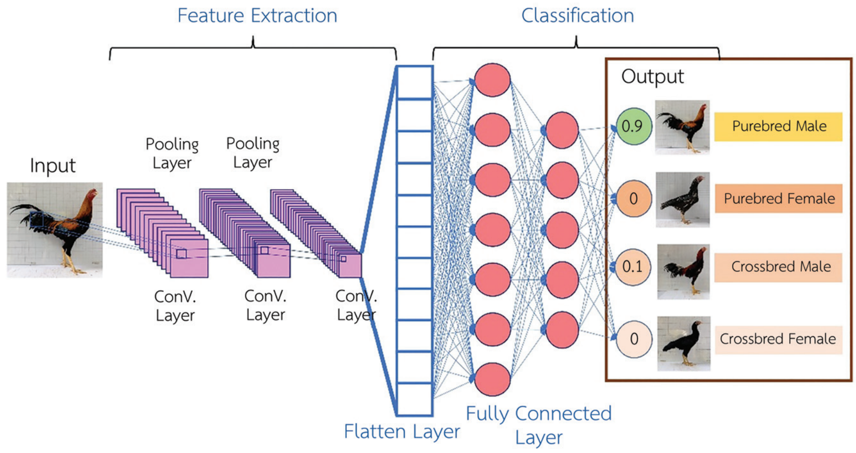


Figure 3 Workflow of the CNN architecture.

Figure 3 illustrates the process of the CNN structure as it performs image classification, specifically focusing on identifying different types of chickens (e.g., Purebred male, Purebred female, Crossbred male, Crossbred female). The process begins with an input image of a chicken, which is fed into the network. Then, the image passes through multiple convolutional layers, each applying a set of filters to generate feature maps that highlight various aspects of the image, such as edges, textures, and patterns. After each convolutional layer, pooling layers down sample the feature maps, reducing their spatial dimensions while retaining essential information. This process helps in making the network more robust to variations in the input image and reduces computational complexity. Once feature extraction is complete, the output from the final pooling layer is flattened into a one-dimensional vector, ready to be processed by fully connected layers. The flattened vector is passed through one or more fully connected layers, where neurons connect to every neuron in the previous layer, allowing the network to learn complex patterns and relationships between the features extracted by the convolutional layers. The final fully connected layer outputs a set of probabilities, each corresponding to a particular class. The class with the highest probability is selected as the predicted label for the input image. In this example, the network correctly identifies the image as a Purebred male with high confidence. The CNN architecture demonstrated in the figure is designed to perform image classification by extracting relevant features from input images and using those features to make accurate predictions. This process is typical in many image classification tasks, where the goal is to categorize images into predefined classes based on learned patterns.

Methodology

This study presents the classification of Thai native chicken breeds using CNNs-based approaches to identify the most suitable architecture for classifying images of Thai native chickens. The following steps have been undertaken.

1. Preparation of Thai Native Chicken Image Data

In this work, Thai native chickens were sourced from two places specializing in breeding and improving chicken breeds under the supervision of experts, as follows.

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1. Kabin Buri Poultry Research and Breeding Center in Prachin Buri managed by the Department of Livestock Development, Thailand, which is dedicated to collecting and developing Leung Hang Khao Thai native chicken breed.

2. Faculty of Agriculture at Khon Kaen University, Thailand, which is involved in the collection and development of the Pradu Hang Dam Thai native chicken breed.

3. The native chickens were kept in cages measuring 50 cm x 80 cm x 1 m, with one chicken per cage, in an open housing environment maintained at around 30 degrees Celsius. During the experiment, feed and clean drinking water were available ad libitum and the diets were provided twice daily at 8:00 AM and 4:00 PM. This research was approved by the Animal Ethics Committee with license number 06/2564/IACUC.

For image collection, purebred Leung Hang Khao chickens from the first source and crossbred chickens between the Leung Hang Khao and Pradu Hang Dam breeds (produced from parent chickens sourced from both locations) were used. A total of 200 chickens (100 males and 100 females), all aged 20 weeks or older, were selected, with 50 chickens from each breed and gender. Images were captured using the OPPO Reno3 Pro smartphone model CPH2037, which has a quad camera system with specifications of 64 MP + 13 MP (Telephoto) + 8 MP (UltraWide) + 2 MP (MONO) and a maximum image resolution of 3,120 x 4,160 pixels.

The photo setup included a white table covered with a white future-board to prevent the chickens from slipping during photography. The background was a whiteboard grid with 1 x 1 square inches for measuring the height of the chickens. A white background was used to ensure a consistent environment for all photos as seen in Figure 4 The distance between the camera and the chickens was set at 80 cm to maintain uniformity in the image capture. A total of 250 images were taken for each group, resulting in 1,000 images in total.

(a) Leung Hang Khao purebred male

(b) Leung Hang Khao purebred female

(c) Crossbred male

(d) Crossbred female

Figure 4 Samples illustrating the Thai native chicken.

2. Verification Tools

This work was conducted using Python programming language with Jupyter Notebook. Jupyter is an Interactive Python that uses a web browser interface, functioning in a server-client model. The backend processor is IPython, and it operates through a JupyterLab server in a Localhost environment (Localhost:8888) (Toomey, 2018; Muttenthaler and Hebart, 2021).

3. CNN Models and Verification

The architectural structure used in this experiment is a simple architecture developed specifically to determine the appropriate architecture for classifying Thai native chickens. The model testing begins by inputting images of Thai native chickens and resizing them from 3,456 x 3,456 pixels to 224 x 224 pixels, then scaling the data to have values between 0 and 1 using the normalization method by dividing the data by 255. The data is divided into three sets: the training set, the validation set, and the test set. The model is tested with the following ratios: 60:20:20, 70:20:10, and 80:10:10. The architecture is created, and the model is tested three times, after which the average is calculated. The number of epochs used in processing is set at three levels: 10, 20, and 50 epochs as seen Figure 5.

In Figure 5, it is illustrated the process of CNN-based classification of Thai native chickens using different CNN architectures. The process begins with an input image of size 3,456 x 3,456 x 3, where 3 represents the RGB color channels. The image undergoes pre-processing, which includes resizing and rescaling. Resizing likely adjusts the image dimensions to match the input requirements of the CNN models, while rescaling normalizes the pixel values, typically between 0 and 1, to standardize the input data. After pre-processing, the image is passed through various CNN architectures, including LeNet-5, CNN1, CNN2, and CNN3. Each architecture processes the image to extract features that help in differentiating between different classes of chickens. The output layer then classifies the image into one of four possible classes, which could represent different breeds of Thai native chickens. The figure emphasizes the experimental approach of using multiple CNN architectures to determine the most effective model for accurate classification.

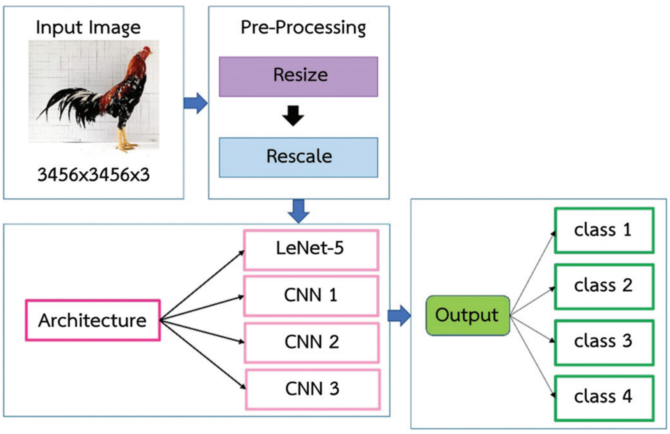


Figure 5 An overview structure of the proposed classification-based CNNs of Thai native chicken with Lenet-5, CNN1, CNN2, and CNN3.

4. Performance Evaluation

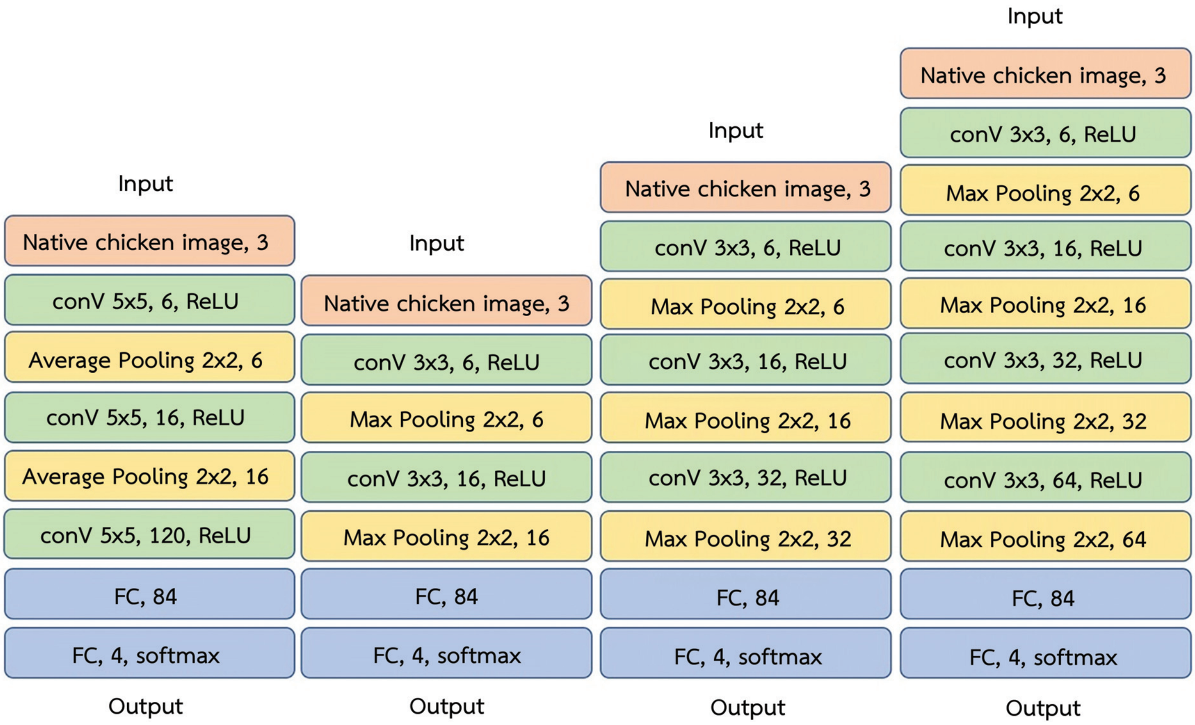
The performance evaluation of the model was conducted using a confusion matrix, including key metrics such as True Positive (TP), representing data correctly predicted as belonging to the considered group; True Negative (TN), which is data correctly predicted as not belonging to the considered group; False Positive (FP), where data is incorrectly predicted as belonging to the considered group; and False Negative (FN), where data is incorrectly predicted as not belonging to the considered group. These prediction values are essential for calculating the accuracy, following the method described in Equation (9) (Krstinić et al., 2020; Arias-Duart et al., 2023), as given by,

In this experiment, 28 images were randomly selected from the dataset of Thai native chicken images, with 7 images per group, to test the prediction accuracy. The number of correctly predicted images by the model was counted, and the percentage accuracy was calculated to measure the model’s performance

Results and Discussion

The application of CNN-based techniques for classifying images of Thai native chickens aims to identify the most suitable architecture for this task. The goal is to gather data to develop efficient tools for classifying the Thai native chickens using images. Four groups of Thai native chickens were used in the experiment: purebred Leung Hang Khao male, purebred Leung Hang Khao female, Crossbred male, and Crossbred female. Four architectures were tested: LeNet-5, CNN1, CNN2, and CNN3 (Figure 6), with different data split ratios for training, validation, and testing (60:20:20, 70:20:10, and 80:10:10) and training periods of 10 epochs, 20 epochs, and 50 epochs. The results showed that the CNN1 architecture, with an 80:10:10 data split and 10 epochs, achieved 100 % accuracy in learning, validation, and testing, predicting correctly 100 % of the time with the shortest processing time. This was likely due to CNN1's minimal convolutional layers, only two. Additionally, CNN1, CNN2, and CNN3 exhibited more stable training and validation accuracy and loss compared to LeNet-5, with stability beginning around the 10^{th} epoch. When training 50 of epochs with an 80:10:10 data split, all four architectures achieved 100 % accuracy. This demonstrates that deep learning using simple CNN architectures can effectively classify images of Thai native chickens, consistent with previous studies using this technique to classify various bird species. For example, the authors in (Singh et al., 2020) used CNNs to classify five bird species from smartphone images taken in natural environments, achieving 93 % learning accuracy and 80 % testing accuracy. The work presented in (Raj et al., 2020) used a modified VGGNet architecture to classify 60 bird species with 93.19 % learning accuracy and 84.91 % testing accuracy. In (Yao et al., 2020), the authors used six different CNN architectures to classify male and female chickens, finding VGG-19 to be the most accurate at 96.85 %. Other studies have applied CNNs to classify wild animals and livestock, achieving high accuracy with architectures like ResNets and LeNet-5.

Although the CNN1 model was able to classify images of Thai native chickens with 100 % accuracy on the test dataset prepared in this study, such results were achieved under highly controlled conditions, such as neutral backgrounds, consistent lighting, and images captured from a standardized angle. Furthermore, the test dataset was relatively limited in size, which may not adequately reflect the model's applicability in diverse real-world environments. Therefore, further experiments using external datasets or real-world scenarios are necessary to validate the model's performance in more varied and challenging contexts.



(a) LeNet-5 (b) CNN1 (c) CNN2 (d) CNN3

Figure 6 The architectures of CNNs-based approaches.

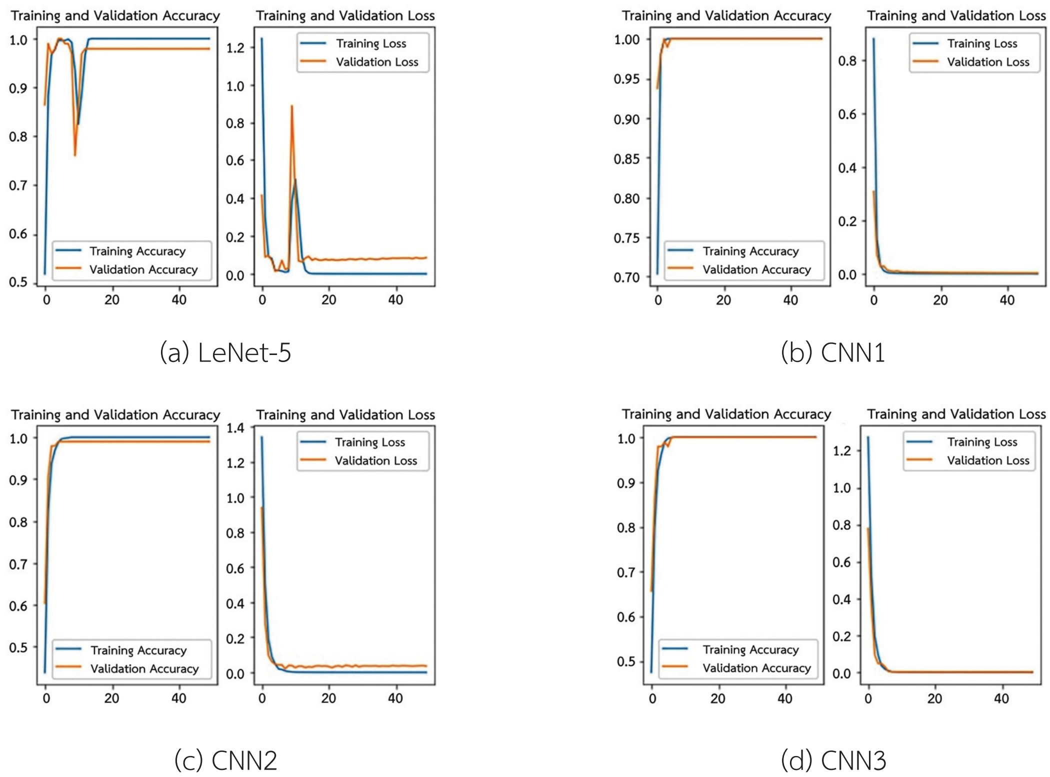


Figure 7 The training and validation accuracy and loss curves for four different convolutional neural network architectures over 50 epochs.

Table 1 presents a comparison of different neural network architectures LeNet-5, CNN1, CNN2, and CNN3 used to classify Thai native chicken. These architectures are evaluated based on various metrics including training accuracy, validation accuracy, testing accuracy, and prediction accuracy across different data splits (60:20:20, 70:20:10, and 80:10:10). Across the architectures, CNN1, with a data split of 80:10:10 and an execution time of 104 seconds, exhibits the most consistent and superior performance, achieving 100 % accuracy across validation, testing, and prediction stages. This indicates that CNN1 is the most efficient and reliable model for this classification task.

Notably, although LeNet-5 also performs well with high accuracy scores across all stages, it falls short compared to CNN1, especially in terms of testing and prediction accuracy where CNN1 consistently hits 100 %. Furthermore, CNN1 achieves these results with a relatively low computation time of 104 seconds, highlighting its efficiency. In contrast, other architectures like CNN2 and CNN3, despite also achieving perfect scores in certain instances, require longer execution times, which may not be optimal for real-time applications. The results suggest that CNN1, particularly with the 80:10:10 split, is the most effective model, balancing high accuracy and low computational cost.

The graphs presented in Figure 7 illustrate the training and validation accuracy, as well as the training and validation loss, for four deep learning models LeNet-5, CNN1, CNN2, and CNN3 over 50 epochs. The accuracy graphs for all models reveal that each architecture rapidly achieves high accuracy within the first 10 epochs, with minimal differences between training and validation accuracy thereafter. This rapid convergence suggests that the models are highly efficient in learning the necessary features for classifying Thai native chickens. Among the architectures, CNN1 and CNN2 demonstrate the most stable and consistent accuracy, achieving nearly perfect alignment between training and validation accuracy early in the training process. LeNet-5, while ultimately achieving high accuracy, exhibits a more noticeable fluctuation in the initial epochs, indicating that it requires more time to stabilize. Similarly, CNN3 shows a slight gap between training and validation accuracy during the initial epochs, which closes as the training progresses.

The loss graphs further corroborate these observations, with all models showing a significant reduction in both training and validation loss within the first few epochs. The graphs for CNN1 and CNN2 display the most rapid decline, with loss values approaching zero early in the training, reflecting their strong generalization capabilities. LeNet-5 and CNN3, however, exhibit a more gradual reduction in loss, particularly in the initial epochs, which aligns with the fluctuations observed in their accuracy graphs. Despite these initial variations, all models converge to low loss values, indicating effective learning. The close alignment of training and validation loss across all models also suggests that there is minimal overfitting, reinforcing the robustness of these architectures. Therefore, the analysis indicates that CNN1 and CNN2 are the most efficient and stable architectures for this classification task, while LeNet-5 and CNN3, though effective, require more epochs to achieve similar performance.

Table 1 Comparison of Four Different CNN Architectures Used to Classify The Thai Native Chickens Which Is Presented As Means ± Standard Deviation (S.D.)

Architecture	Ratio	Epoch	Time (s)	Training Accuracy (%)	Validation Accuracy (%)	Testing Accuracy (%)	Prediction (%)
LeNET-5	60:20:20	10	237	99.33±0.51	97.92±0.27	97.77±0.25	97.50±0.28
		20	420	96.38±0.89	96.35±0.85	95.98±0.59	95.00±0.95
		50	754	100±0.00	97.40±0.81	97.32±0.84	97.75±1.08
	70:20:10	10	237	100±0.00	98.96±0.51	99.22±0.33	100±0.00
		20	425	100±0.00	98.96±0.72	99.22±0.26	99.33±0.51
		50	746	100±0.00	96.88±0.58	96.88±0.89	99.33±0.51
	80:10:10	10	236	100±0.00	100±0.00	97.92±0.47	100±0.00
		20	410	99.87±0.29	99.48±0.05	98.66±0.51	99.33±0.51
		50	748	100±0.00	97.92±0.27	100±0.00	100±0.00
CNN1	60:20:20	10	106	100±0.00	98.96±0.87	98.66±0.51	100±0.00
		20	141	100±0.00	98.44±0.39	99.11±0.32	100±0.00
		50	347	100±0.00	98.68±0.93	95.26±0.75	97.50±0.95
	70:20:10	10	102	100±0.00	99.48±0.53	100±0.00	100±0.00
		20	160	100±0.00	100±0.00	100±0.00	100±0.00
		50	347	100±0.00	100±0.00	98.96±0.40	100±0.00
	80:10:10	**10**	**104**	**100±0.00**	**100±0.00**	**100±0.00**	**100±0.00**
		20	157	100±0.00	100±0.00	99.22±0.29	100±0.00
		50	346	100±0.00	100±0.00	99.22±0.25	100±0.00
CNN2	60:20:20	10	121	100±0.00	100±0.00	100±0.00	100±0.00
		20	168	100±0.00	100±0.00	98.86±0.36	100±0.00
		50	395	100±0.00	98.96±0.75	98.96±0.12	100±0.00
	70:20:10	10	119	100 ± 0.00	100 ± 0.00	100 ± 0.00	100 ± 0.00
		20	172	100±0.00	99.22±0.32	98.53±0.39	100±0.00
		50	396	100±0.00	98.75±0.85	100±0.00	100±0.00
	80:10:10	10	115	100±0.00	98.96±0.36	99.22±0.22	100±0.00
		20	178	100±0.00	100±0.00	99.22±0.29	100±0.00
		50	392	100±0.00	98.96±0.98	100±0.00	100±0.00
CNN3	60:20:20	10	122	98.86±1.09	92.71±0.85	92.97±0.95	92.50±0.59
		20	184	100±0.00	98.96±0.78	100±0.00	100±0.00
		50	415	100±0.00	98.25±0.74	100±0.00	100±0.00
	70:20:10	10	119	98.86±0.83	92.71±0.46	92.97±1.05	95.00±0.19
		20	191	100±0.00	98.96±0.83	100±0.00	100±0.00
		50	416	100±0.00	99.22±1.01	100±0.00	100±0.00
	80:10:10	10	114	99.87±0.46	100±0.00	100±0.00	100±0.00
		20	186	100±0.00	98.96±0.69	99.22±1.05	100±0.00
		50	402	100±0.00	100±0.00	100±0.00	100±0.00

Figure 8 The confusion matrix for the performance evaluation of the classification model.

The confusion matrix in Figure 8 shows the classification performance of the best model for distinguishing among four categories of Thai native chickens: purebred male, purebred female, crossbred male, and crossbred female. The matrix demonstrates perfect classification accuracy, as all 28 images in each class were correctly identified without any misclassifications. This result highlights the model's ability to effectively learn and distinguish between the subtle differences in the visual features of the chickens across different breeds and genders. The complete diagonal alignment, with no off-diagonal errors, further emphasizes the robustness and precision of the model, validating its suitability for the task of poultry classification.

Conclusion

This paper introduced the employment of deep learning techniques with CNNs for classifying Thai native chickens, specifically the Leung Hang Khao breed. The findings demonstrated that the CNN1, which was of simple design and setting, was the fastest and most efficient in classifying Thai native chicken images. The CNN1 architecture achieved 100 % accuracy in learning, validation, testing, and prediction, making it useful for verifying the Thai native chicken breeds and reducing the variability in judgments made by committee members with differing levels of experiences during Thai native chicken competitions. Moreover, the introduced technique aided farmers in accurately selecting breeding pairs for preserving Thai native chicken breeds.

Future work will focus on increasing the number of datasets for other Thai native chicken breeds and may involve refining the deep learning model to improve its efficiency and accuracy in classifying a variety of the native chicken breeds.

References

Arias-Duart, A., Mariotti, E., Garcia-Gasulla, D. and Alonso-Moral, J.M. (2023). A Confusion Matrix for Evaluating Feature Attribution Methods. In *2023 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*, 3709-3714. http://doi.org/10.1109/CVPRW59228.2023.00380

Buranawit, K., Chailungka, C., Wongsunsri, C. and Laenoi, W. (2016). Phenotypic Characterization of Thai Native Black-Bone Chickens Indigenous to Northern Thailand. *The Thai Journal of Veterinary Medicine*, 46(4), 547-554. https://he01.tci-thaijo.org/index.php/tjvm/article/view/73774/59525

Dorji, N. and Sunar, S. (2014). Morphometric Variations Among Five Bhutanese Indigenous Chickens (*Gallus domesticus*). *Journal of Animal and Poultry Sciences*, 3(3), 76-85.

Dorji, N., Duangjinda, M. and Phasuk, Y. (2012). Genetic Characterization of Bhutanese Native Chickens Based on an Analysis of Red Junglefowl (*Gallus gallus gallus* and *Gallus gallus spadecieus*), Domestic Southeast Asian and Commercial Chicken Lines (*Gallus gallus domesticus*). *Genetics and Molecular Biology*, 35(3), 603-609. https://doi.org/10.1590/S1415-47572012005000039

Fumihito, A., Miyake, T., Sumi, S.i., Takada, M., Ohno, S. and Kondo, N. (1994). One Subspecies of the Red Junglefowl (*Gallus gallus gallus*) Suffices as the Matriarchic Ancestor of All Domestic Breeds. *Proceedings of the National Academy of Sciences*, 91(26), 12505-12509. https://doi.org/10.1073/pnas.91.26.12505

Hansen, M.F., Smith, M.L., Smith, L.N., Salter, M.G., Baxter, E.M., Farish, M. and Grieve, B. (2018). Towards On-Farm Pig Face Recognition Using Convolutional Neural Networks. *Computers in Industry*, 98, 145-152. https://doi.org/10.1016/j.compind.2018.02.016

Hata, A., Nunome, M., Suwanasopee, T., Duengkae, P., Chaiwatana, S., Chamchumroon, W., Suzuki, T., Koonawootrittriron, S., Matsuda, Y. and Srikulnath, K. (2021). Origin and Evolutionary History of Domestic Chickens Inferred from a Large Population Study of Thai Red Junglefowl and Indigenous Chickens. *Scientific Reports*, 11, 2035. https://doi.org/10.1038/s41598-021-81589-7

Katano, T., Shimogiri, T., Kawabe, K. and Okamoto, S. (2011). Genetic Diversity and Population Structure of Indonesian Native Chickens Based on Single Nucleotide Polymorphism Markers. *Poultry Science*, 90(11), 2471-2478. https://doi.org/10.3382/ps.2011-01450

Khan, R.H., Kang, K.W., Lim, S.J., Youn, S.D., Kwon, O.J., Lee, S.H. and Kwon, K.R. (2020). Animal Face Classification Using Dual Deep Convolutional Neural Betwork. *Journal of Korea Multimedia Society*, 23(4), 525-538. https://doi.org/10.9717/kmms.2020.23.4.525

Khumpeerawat, P., Duangjinda, M. and Phasuk, Y. (2021). Factors Affecting Gene Expression Associated with the Skin Color of Black-Bone Chicken in Thailand. *Poultry Science*, 100(11), 101440. https://doi.org/10.1016/j.psj.2021.101440

Kittichai, V., Kaewthamasorn, M., Thanee, S., Jomtarak, R., Klanboot, K., Naing, K.M., Tongloy, T., Chuwongin, S. and Boonsang, S. (2021). Classification for Avian Malaria Parasite *Plasmodium gallinaceum* Blood Stages by Using Deep Convolutional Neural Networks. *Scientific Reports*, 11, 16919. https://doi.org/10.1038/s41598-021-96475-5

Krstini´c, D., Braovi´c, M., Šeri´c, L. and Boži´c-Štuli´C,D. (2020). Multi-Label Classifier Performance Evaluation with Confusion Matrix. *Computer Science & Information Technology*, 1, 1-14. https://doi.org/10.5121/csit.2020.100801

Laenoi, W., Kunkalw, W. and Buranawit, K. (2015). Phenotypic Characterization and Farm Management of Indigenous Chicken Reared in Highland Region of Northern Thailand. *Agriculture and Agricultural Science Procedia*, 5, 127-132. https://doi.org/10.1016/j.aaspro.2015.08.019

Lecun, Y., Bottou, L., Bengio, Y. and Haffner, P. (1998). Gradient-Based Learning Applied to Document Recognition. *Proceedings of the IEEE*, 86(11), 2278-2324. https://doi.org/10.1109/5.726791

Liu, Y.P., Wu, G.S., Yao, Y.G., Miao, Y.W., Luikart, G., Baig, M., Beja-Pereira, A., Ding, Z.L., Palanichamy, M.G. and Zhang, Y.P. (2006). Multiple Maternal Origins of Chickens: Out of the Asian Jungles. *Molecular Phylogenetics and Evolution*, 38(1), 12-19. https://doi.org/10.1016/j.ympev.2005.09.014

Mbelwa, H., Machuve, D. and Mbelwa, J. (2021). Deep Convolutional Neural Network for Chicken Diseases Detection. *International Journal of Advanced Computer Science and Applications*, 12(2), 759-765. https://doi.org/10.14569/IJACSA.2021.0120295

Mekchay, S., Supakankul, P., Assawamakin, A., Wilantho, A., Kluabmongkol, W. and Tongsima, S. (2014). Population Structure of Four Thai Indigenous Chicken Breeds. *BMC Genetics*, 15, 1-9. https://doi.org/10.1186/1471-2156-15-40

Mou, C., Liang, A., Hu, C., Meng, F., Han, B. and Xu, F. (2023). Monitoring Endangered and Rare Wildlife in the Field: A Foundation Deep Learning Model Integrating Human Knowledge for Incremental Recognition with Few Data and Low Cost. *Animals*, 13(20), 3168; https://doi.org/10.3390/ani13203168

Muttenthaler, L. and Hebart, M.N. (2021). THINGSvision: a Python Toolbox for Streamlining the Extraction of Activations from Deep Neural Networks. *Frontiers in Neuroinformatics*, 15, 679838. https://doi.org/10.3389/fninf.2021.679838

Okumura, F., Shimogiri, T., Kawabe, K., Okamoto, S., Nishibori, M., Yamamoto, Y. and Maeda, Y. (2006). Gene Constitution of South-East Asian Native Chickens, Commercial Chickens and Jungle Fowl Using Polymorphisms of Four Calpain Genes. *Animal Science Journal*, 77(2), 188-195. https://doi.org/10.1111/j.1740-0929.2006.00336.x

Phasouk, A., Sakkatat, P., Kruekum, P. and Fongmul, S. (2021). The Situation of Farmers Rearing Native Chickens in Muang La, Udomxay Province, Laos PDR. *Rajabhat Chiang Mai Research Journal*, 22(2), 20-34. https://so05.tci-thaijo.org/index.php/cmruresearch/article/view/248813/171660

Pramual, P., Meeyen, K., Wongpakam, K. and Klinhom, U. (2013). Genetic Diversity of Thai Native Chicken Inferred from Mitochondrial DNA Sequences. *Tropical Natural History*, 13(2), 97-106. https://li01.tci-thaijo.org/index.php/tnh/article/view/103035/82579

Raj, S., Garyali, S., Kumar, S. and Shidnal, S. (2020). Image Based Bird Species Identification Using Convolutional Neural Network. *International Journal of Engineering Research & Technology (IJERT)*, 9(6), 346-351. https://www.ijert.org/research/image-based-bird-species-identification-using-convolutional-neural-network-IJERTV9IS060279.pdf

Ren, Y., Huang, Y., Wang, Y., Zhang, S., Qu, H., Ma, J., Wang, L. and Li, L. (2022). A High-Performance Day-Age Classification and Detection Model for Chick Based on Attention Encoder and Convolutional Neural Network. *Animals*, 12(18), https://doi.org/10.3390/ani12182425

Rotimi, E., Egahi, J. and Adeoye, A. (2016). Phenotypic Characterization of Indigenous Chicken Population in Gwer-West, Benue State, Nigeria. *World Scientific News*, 53(3), 343-353.

Samek, W., Binder, A., Montavon, G., Lapuschkin, S. and Müller, K.R. (2016). Evaluating the Visualization of What a Deep Neural Network Has Learned. *IEEE Transactions on Neural Networks and Learning Systems*, 28(11), 2660-2673. https://doi.org/10.1109/TNNLS.2016.2599820

Sawai, H., Kim, H.L., Kuno, K., Suzuki, S., Gotoh, H., Takada, M., Takahata, N., Satta, Y. and Akishinonomiya, F. (2010). The Origin and Genetic Variation of Domestic Chickens with Special Reference to Junglefowls *Gallus g. gallus* and *G. varius*. *PloS One*, 5(5), https://doi.org/10.1371/journal.pone.0010639

Schork, I., Zamansky, A., Farhat, N., de Azevedo, C.S. and Young, R.J. (2024). Automated Observations of Dogs' Resting Behaviour Patterns Using Artificial Intelligence and Their Similarity to Behavioural Observations. *Animals*, 14(7), https://doi.org/10.3390/ani14071109

Shimogiri, T., Nishida, N., Kudo, M., Niwa, K., Nishibori, M., Kinoshita, K., Okamoto, S., Maeda, Y., Tokunaga, K. and Yasue, H. (2012). Genetic Relationships Between Japanese Native and Commercial Breeds Using 70 Chicken Autosomal SNP Genotypes by the DigiTag2 Assay. *Animal Genetics*, 43(1), 98-103. https://doi.org/10.1111/j.1365-2052.2011.02206.x

Singh, A., Jain, A. and Rai, B.K. (2020). Image Based Bird Species Identification. *International Journal of Research in Engineering, IT and Social Sciences*, 10(4), 17-24.

Siriwadee, P., Wirot, L., Thanapol, P. and Wirawan, N. (2023). Genetic Diversity Among Five Native Thai Chickens and Khiew-Phalee Chickens in Lower-Northern Thailand Using Mitochondrial DNA Barcodes. *Biodiversitas*, 24(4), 1962-1970. https://doi.org/10.13057/biodiv/d240404

Sozzi, M., Pillan, G., Ciarelli, C., Marinello, F., Pirrone, F., Bordignon, F., Bordignon, A., Xiccato, G. and Trocino, A. (2023). Measuring Comfort Behaviours in Laying Hens Using Deep-Learning Tools. *Animals*, 13(1), https://doi.org/10.3390/ani13010033

Thinh, N.H., Tuan, H.A., Dang, P.K. and Doan, B.H. (2015). Multi-Spurred Chicken Breed and Livelihood of Ethnic People in North Vietnam: Characterisation and Prospects. *The 1th International conference on Native chicken Journal.* February 23-25, Centara Hotel Khon Kaen, Thailand.

Toomey, D. (2018). *Learning Jupyter 5: Explore Interactive Computing Using Python, Java, JavaScript, R, Julia, and JupyterLab* (2nd Ed). Packt Publishing Ltd.

Vanhala, T., Tuiskula-Haavisto, M., Elo, K., Vilkki, J. and Maki-Tanila, A. (1998). Evaluation of Genetic Variability and Genetic Distances Between Eight Chicken Lines Using Microsatellite Markers. *Poultry Science*, 77(6), 783-790. https://doi.org/10.1093/ps/77.6.783

Villa, A.G., Salazar, A. and Vargas, F. (2017). Towards Automatic wild Animal Monitoring: Identification of Animal Species in Camera-Trap Images Using Very Deep Convolutional Neural Networks. *Ecological Informatics*, 41, 24-32. https://doi.org/10.1016/j.ecoinf.2017.07.004

Wang, K., Chen, C. and He, Y. (2020). Research on Pig Face Recognition Model Based on Keras Convolutional Neural Network. *IOP Conference Series Earth and Environmental Science*. 474(3), https://doi.org/10.1088/1755-1315/474/3/032030

Wiyabot, T. and Kiattinarueyut, S. (2022) Development and Identifying Quantitative and Quantities Traits for Breeding of Samae Dam Chicken (*Gallus gallus*), Thailand: Diversity of Phenotypic Characteristics. *Journal of the Hellenic Veterinary Medical Society*, 73(4), 4763-4772. https://doi.org/10.12681/jhvms.27405

Xu, N., Ma, Z., Xia, Y., Dong, Y., Zi, J., Xu, D., Xu, F., Su, X., Zhang, H. and Chen, F. (2024). A Serial Multi-scale Feature Fusion and Enhancement Network for Amur Tiger Re-Identification. *Animals*, 14(7), https://doi.org/10.3390/ani14071106

Yaemkong, S., Phromnoi, S., Mingchai, C. and Jongjitvimol, T. (2024). Characterization of Phenotypic Variation in Indigenous Chicken Populations in Lower Northern Thailand to Improve Chicken Breeding. *International Journal of Zoology*, 2024, https://doi.org/10.1155/2024/9985076

Yao, Y., Yu, H., Mu, J., Li, J. and Pu, H. (2020). Estimation of the Gender Ratio of Chickens Based on Computer Vision: Dataset and Exploration. *Entropy*, 22(7), https://doi.org/10.3390/e22070719

Yeamkong, S., Tangmo, S., Howhan, S., Gothom, P., Jaipong, P., Incharoen, T. and Muangtong, S. (2021). Effects of *Sesbania Grandiflora* (L.) DESV, *Spathodea Campanulate* (P.) Beauv. and *Cochlospermum Regium* (L.) Alston. flowers supplementation layer diet on egg production, egg quality and blood parameters. *Life Sciences and Environment Journal*, 22, 238-251. https://ph01.tci-thaijo.org/index.php/psru/article/view/244717/167534

Zhang, L., Han, G., Qiao, Y., Xu, L., Chen, L. and Tang, J. (2023). Interactive Dairy Goat Image Segmentation for Precision Livestock Farming. *Animals*, 13(20), https://doi.org/10.3390/ani13203250