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Coleoptera Classification Using Convolutional Neural Network and Transfer Learning

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Abstract *- This study presents the use of convolutional neural networks and transfers learning for classifying Coleoptera specimens. The images used as a dataset in this study were gathered from previous research work and various repositories. Four classes were used to train the convolutional neural network, with the Buprestidae, Carabidae, Cerambycidae, and Coccinellidae families. Since the dataset was rather imbalanced, images were preprocessed to augment the dataset and minimize the probability of overfitting. Transfer learning was implemented by using the InceptionV3 pre-trained model. The final layer was retrained using the new dataset while retaining its prior knowledge base. After the training and validation of the new model, an average of 97% classification accuracy was attained.*

Keywords — *Beetle Classification, Coleoptera, Convolutional Neural Network, Inception Network, Transfer Learning*

I. INTRODUCTION

The Coleoptera family is considered the most diverse and dominant species of insects in the animal kingdom [1]. However, despite its abundance, Coleoptera biodiversity remains threatened by various naturogenic pressures and anthropogenic degradations [2]–[6]. Various conservation works are proposed as researchers found Coleoptera studies to be essential in understanding biodiversity patterns by using it as a model taxon in this effort [7].

With the aim to strengthen Coleoptera research and conservation, the University of Mindanao in Davao City, Philippines, led the establishment of the Coleoptera Research Center (CRC) on its campus. CRC is known to be the first center in the Philippines dedicated to coleopterological studies. Along with the establishment of the center is the founding of the Philippine Coleopterological Network (PhilColNet), which enjoins scientists, advocates, and hobbyists alike who share profound interests in the discovery, classification, and conservation of Philippine Coleoptera [8].

The center currently houses over a thousand species in its collections. Moreover, the in-house researchers are still in the process of augmenting its Coleoptera database. Biologists and volunteers of the CRC continue to conduct expeditions by visiting various mountainous and heavy-forested landscapes, such as local UNESCO heritage sites, in search of Coleoptera specimens. With the expanding collection of the research center, the need for optimal classification is essential.

Classification is regarded as an important decision-making tool. However, the accurate classification remains a challenge for some due to the lack of knowledge and high similarity index of features [9]. Without the advent of technology, the traditional morphological classification system is observed to be a tedious, costly, and time-consuming process [10]–[12]. It requires extensive taxonomic knowledge and expertise of trained taxonomists and technicians whose numbers have decreased over the years [13], [14].

The use of a neural network for automated classification would help the center and its researchers in their expeditions and laboratory work. Therefore, the automation of the classification process could increase classification accuracy, improve scalability on the analysis, and minimize its cost [15], [16].

However, a simple classification model is not enough since the research center is actively adding more specimens to their collections. There is a constant need to create a new classification model for every new species discovered. To remedy this, the use of transfer learning, which has the ability to transfer existing knowledge to new conditions [17], is proposed.

Transfer learning is an approach in deep learning wherein a pre-trained model developed for a particular task is reused as a starting point for a new model. With new species being discovered every time, and given the computational costs of training neural networks, it is more efficient to reuse an existing model for training new classes than to start from scratch. Convolutional neural networks paired with transfer learning could create a more finely tuned classification model, thus this study. The conduct of this study would benefit not just the Coleoptera Research Center of the University of Mindanao but would also support the preservation of Coleoptera biodiversity in the Philippines.

II. LITERATURE REVIEW

Kasinathan et al. [18] used various machine learning techniques to develop a field crop insect detection and classification model. The study assessed the performance of the Naïve Bayes (NB) algorithm, k-nearest neighbors (KNN) algorithm, support vector machine (SVM) algorithm, artificial neural networks (ANN), and convolutional neural networks (CNN). Simulations were executed using two datasets which were composed of 9 and 24 insect classes for the first and second datasets, respectively. Results of the study have revealed that the use of CNN obtained the highest classification accuracy when compared with other machine learning algorithms. The CNN model attained 91.5% and 90% classification accuracy for the first and second datasets, respectively. Further, the paper [19] presented a deep learning approach for detecting and classifying stored-grain through an improved inception network. In this study, a 27-layer CNN was utilized to extract image features and used a Softmax function for multiclass classification. Moreover, real-time insect detection and analysis were achieved through an Online Insect Trapping Device (OITD) and Faster R-CNN. The experiment was conducted using 739 images of stored-grain insects to develop the classification model. Findings showed that the improved inception network achieved an 88% mean average precision.

Another study used image processing and ANN for the classification of various butterfly species. The dataset of 140 140 butterfly images was preprocessed to extract relevant texture features with the use of the average gray level co-occurrence matrix (GLCM). This technique identifies the contrast, entropy, homogeneity, correlation, energy, and RGB color features of the images. After the training and testing of the proposed method, a 92.85% classification accuracy was achieved [20]. Moreover, a deep learning model was developed by Wu et al. [21] in 2019 for detecting food contaminating beetle species. The convolutional neural network was trained and tested using 15 beetle species with 6900 elytra microscopic images. In terms of network architecture, 4 fully connected hidden layers comprised the dense block. Each of these layers was set to have 1024, 512, 256, and 128 nodes, respectively. A dropout rate of 0.8 was also added after the first layer. Furthermore, the activation function used for each layer was the Rectified Linear Unit (ReLU). The results of the study obtained an overall 83.8% classification accuracy.

III. METHODOLOGY

A. Dataset

In this paper, 1,327 beetle images were collected from the study of [22] and online repositories from [23], [24]. All images were organized in a local directory according to their family, wherein 4 classes were identified. The sample images for each identified class are shown in Fig. 1, while the number of instances per class is presented in Fig. 2. As observed, the classes of Cerambycidae and Carabidae have the most number of instances, while the other two classes had approximately just half. Having an imbalanced dataset may contribute to the overfitting of the neural network during its training [25]. To address this, data augmentation was implemented to increase training samples [26], [27].

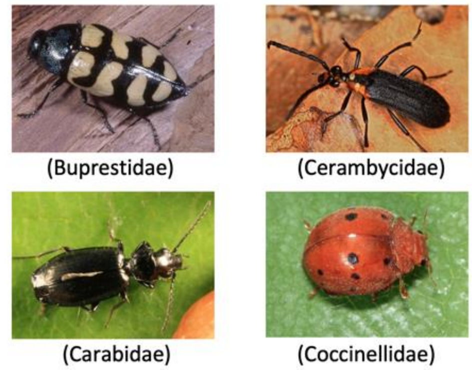

Fig. 1 Sample images per class

The images were preprocessed using a Python script to expand each class to contain at least 1000 instances. The preprocessing method utilized a randomized augmentation approach of rotating the image, adding noise, flipping horizontally, flipping vertically, and adjusting exposure. After the script was executed, the total number of instances was increased to 4000.

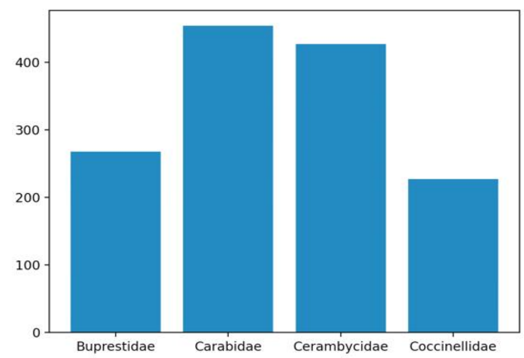

Fig. 2 Class distribution before image augmentation

B. Convolutional Neural Network

The Convolutional Neural Network (CNN) is a type of deep neural network which is extensively utilized in the field of computer vision and image processing [28]. The network is inspired by the biological processes of the human brain that is intelligent enough to identify different objects through using previous observations [29]. A generic CNN architecture is composed of input layers, hidden layers with multiple convolutional layers, pooling layers, fully connected layers, and an output layer for classification. Sample architecture of a convolutional neural network is presented in Fig. 3.

The input layer accepts images as input data. Usually, these images are preprocessed before they are passed onto the layer. The convolutional layer, which is also known as the transformation layer, performs convolution processes to the input data using a method called feature selection. The method creates a feature map with the use of filters with a varying size of either 1x1, 3x3, 5x5, or 7x7. A sample convolutional process is presented in Fig. 4, wherein a 3x3 filter is multiplied to the input image.

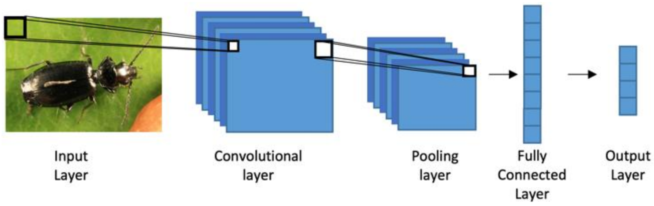

Fig. 3 Convolutional neural network

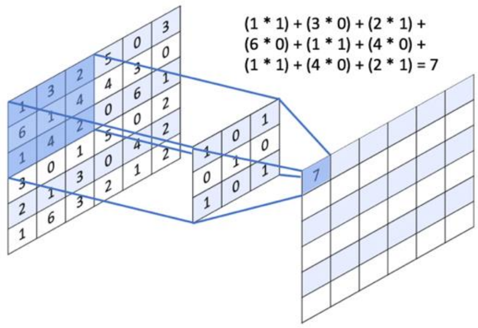

Fig. 4 Convolutional process

The pooling layer in a CNN combines nearby units using a pooling window to decrease the input size to the succeeding layer, thereby reducing dimensions. The common approaches used for the pooling process are average pooling and max pooling. A sample pooling operation using a window of 2 is shown in Fig. 5.

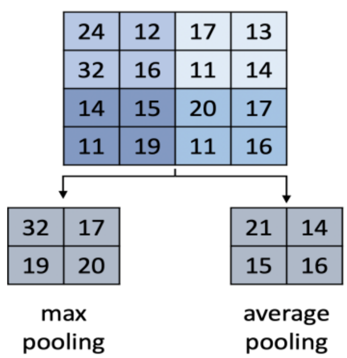

Fig. 5 Max and average pooling using a 2x2 filter

All features extracted from the convolutional and pooling layers are flattened together at the fully connected layers. An activation function is then executed in the fully connected layer to perform a classification task. Some approaches include TanH, ReLU, Softmax, or Sigmoid, among others. Dropout layers may also be added to prevent overfitting by eliminating some of the neuron connections [25]. The output layer usually uses a Softmax function to produce probability-based values in classifying an object.

C. Transfer Learning

Transfer learning is a deep learning approach generally used for natural language processing and computer vision. The objective of transfer learning is to accelerate the training and minimize cost by using an existing prediction model as a starting point so as to save time and resources. Traditional machine learning models work well if the training data are under the same feature space and data distribution. However, traditional approaches may not work best if the feature space and data distribution change frequently. This would then require occasionally develop a new classification model from the ground up, which is a very expensive task.

Transfer learning is applied by reusing a pre-trained model and its weights into a new model. Further, these weights may be kept fixed, fine-tuned, or replaced entirely during training. The most common pre-trained models are VGG [30], Inception [31], and ResNet [32], which were trained using a visual database called ImageNet[33] containing more than 14 million images. In this study, the use of the Inceptionv3 pre-trained model is observed.

Inceptionv3 is a deep convolutional neural network widely used in computer vision for object detection and image analysis. It is known as the 3rd version of the Inception networks developed by Google. The model was originally trained with 1,000 classes and 1 million images from ImageNet. To utilize transfer learning for Inceptionv3, the final layer of the existing model is retrained with a new dataset. This enables the network to maintain its previous knowledge base while learning new feature spaces efficiently with lesser training time and computational power [30]. The implementation of transfer learning in this study is presented in Fig. 6.

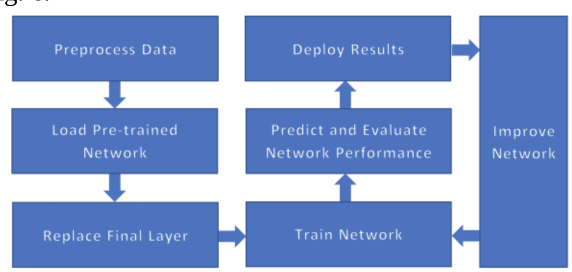

Fig. 6 Transfer learning framework

IV. RESULTS AND DISCUSSION

Simulations were executed on a laptop with 10th gen core-i5 processor and 16GB RAM using Python and Keras library. The dataset was split into three subsets: 70% training, 15% testing, and 15% validation sets. All images were resized to 299x299 as input to the Inception network. The retraining of the model was set to run for 50 epochs in a batch size of 128 and with an early stopping rule. Moreover, a learning rate of 0.00001 was set using the Adam optimizer algorithm with a time-based decay presented in (1) for better optimization and generalization of the model [34]. A standard dropout regularization technique was also implemented at a 0.5 probability.

$$lr = lr \times \left(\frac{1}{1 + 0.1 \times epoch}\right) \tag{1}$$

The training of the model ended at 24 epochs due to the early stopping mechanism. To assess the performance of the model training, its accuracy and loss curves were obtained and are presented in Fig. 7 and Fig. 8, respectively. As observed, the model has been trained successfully with good fit and has neither overfitted nor under-fitted during its training and validation.

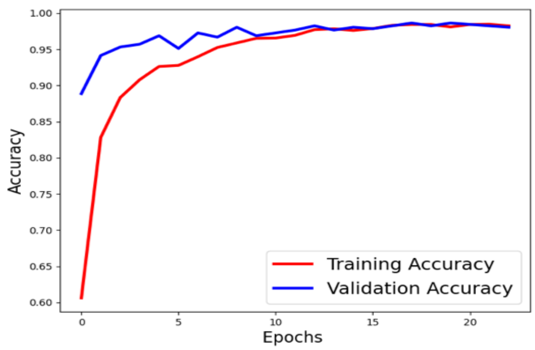

Fig. 7 Accuracy curves

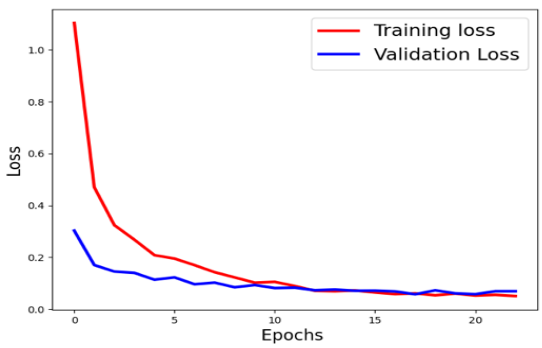

Fig. 8 Loss curves

A confusion matrix was also generated to retrieve the overall precision, recall, and F1 scores for each of the classes. The findings are presented in Table 1 and Fig. 9. The results reveal that the classification of the Coccinellidae class performed best at 98% accuracy. On the other hand, the prediction accuracy for the Carabidae and Cerambycidae classes attained a similar rate of 97%. It can also be observed that most of the prediction errors occur from the Buprestidae class, which obtained the least accuracy among others at 95%. Overall, an average accuracy score of 97% has been attained.

Table 1 Normalized Confusion Matrix

Class	**Precision**	**Recall**	**F1-score**
Buprestidae	0.94	0.95	0.95
Carabidae	0.98	0.97	0.98
Cerambycidae	0.97	0.97	0.97
Coccinellidae	0.99	0.98	0.98
Model Accuracy			0.97
Macro Average	0.97	0.97	0.97
Weighted Average	0.97	0.97	0.97

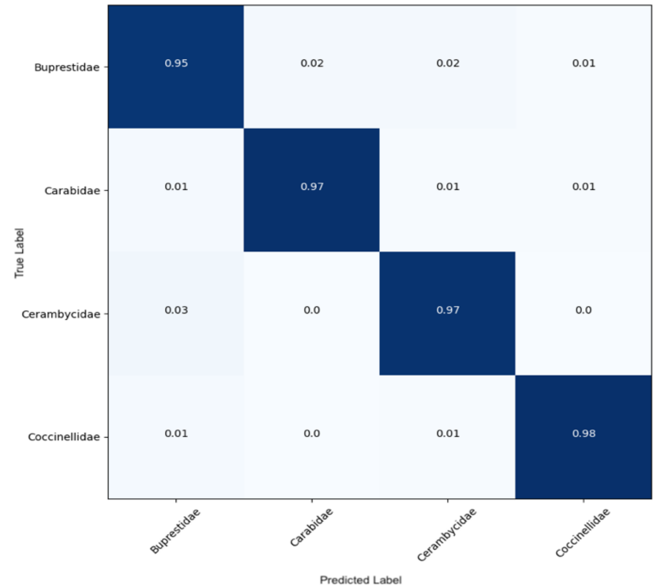

Fig. 9 Confusion matrix

V. CONCLUSION AND RECOMMENDATION

In this study, a transfer learning-based approach is applied in the classification of beetle specimens using convolutional neural networks. The pre-trained InceptionV3 model was used as a baseline for generating a new prediction model based on the collected image dataset. With the 4 classes utilized for training, an average of 97% classification accuracy was obtained during validation. This shows that the objective of developing a model classifying Coleoptera specimens with the use of convolutional neural networks and Inception-based transfer learning was successfully accomplished. It is recommended that future researchers include more classes and use other optimization methods [35] to attain a better classification performance.

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