Ornithological Identification from Images Using Convolutional Neural Networks

By Jialin Wang

AUTHOR BIO

Jialin Wang is a current high school senior attending University High School in California. He started programming at the age of nine and has experience in many programming languages, including Python, Java, and C++. Jialin has excelled in many academic fields at school, especially STEM fields such as computer science, math, and physics. Outside of the classroom, Jialin is a member of University High School's Birding Club where he grew an ardent passion about birding and the environment. In the future, Jialin plans on majoring in computer science and using his skills in programming to address environmental problems and achieve sustainability.

ABSTRACT

As society works towards solutions to address environmental concerns, a crucial task emerges: the conservation of species, including avian species, through precise identification and monitoring. This paper shows that it is necessary to develop a quick and efficient way to identify birds in pictures. This project aims to improve the efficiency of bird identification by using a convolutional network to identify 10 distinct species of birds based on their visual representations. The results of the model are good: eventually, the model achieved decent performance indicators, including an accuracy of 0.75, macro average precision of 0.76, and macro average recall of 0.75. These metrics reflect the model's ability to not only correctly identify birds but also minimize false identifications. Notably, this model demonstrates remarkable performance in classification of common birds such as the American Crow and the California Gull. Moreover, it can also distinguish some nuances between distinct species of birds and distinguish the bird from the background environment.

Keywords: Computer Science, Machine Learning, Neural Network, Convolutional Neural Network, Image Classification, Image Identification, Bird, Birding, Ornithology

INTRODUCTION

During the long journey of species evolution, birds have played a significant role in ecosystems throughout the world. They can also be a significant indicator of habitat health and species richness (Niemi, Hanowski, Lima, Nicholls, & Weilland, 1997). Understanding the differences between different bird species also allows biologists to understand the evolutionary process and the mysteries of life. Ornithology, the study of birds, is popular among many people, partly because non-professionals can also play a significant role, such as observing, recording, and identifying birds (Encyclopedia Britannica, Inc., 2018; Storer, Gill, & Rand, 2018). Anthropogenic factors, including pollution, diseases, and climate change, are posing a threat to many types of birds, such as endangered birds of prey (Azzarello & Van Vleet, 1987; Crick, 2004; Tella, 2001).

As concerns for environmental conservation grow, it is increasingly necessary to identify species for environmental conservation purposes. Identification of birds has been a problem for ornithologists, birders, biologists, and environmentalists alike. The main challenge of bird identification is the sheer variety of bird taxonomy and the nuanced differences between species. This presents a formidable challenge for many, which can be solved with various machine learning algorithms, including convolutional neural networks, a type of algorithm that excels in extracting features from images and classifying them into categories, which will be the focus of this paper. In recent years, machine learning has emerged as a new technique for various tasks, including image classification. This research will attempt to solve a bird identification problem based on images using machine learning techniques.

Previous research on this topic has used machine learning. For example, one previous research by Allison M. Horst, Alison Presmanes Hill, and Kristen B. Gorman aimed to classify three different penguin species based on data collected from Palmer Archipelago islands. However, the classes were limited to Gentoo, Chinstrap, and Adelie penguins. The dataset was textual instead of image. (Horst, Hill & Gorman, 2022).

This research project is an attempt to improve upon previous research. There are 10 different bird species the model will classify.

1. American crow (Corvus brachyrhynchos): A highly intelligent and social bird found in most parts of the US that feeds on a variety of food sources, from berries to little birds. They often work together for food and are active in many rural and urban areas (Montgomery, 2023).

2. Blue Jay (Cyanocitta cristata): This species is found to the east of the Rockies, with a perky crest and blue plumage. They often feed on nuts and insects, and often harvest acorns and hoard them in the ground (National Audubon Society, 2023).

3. Vermillion flycatcher (Pyrocephalus rubinus): as its name suggests, this is a subtype of the tyrant flycatchers in which males typically show a bright red color. They feed on insects by catching them while in flight in a behavior known as flycatching (National Audubon Society, 2023).

4. Western Grebe (Aechmophorus occidentalis): a type of waterfowl that is found in western US and Mexico. It is signified by its red eyes, red beak, and is well known for its unique mating dance in which the male and female “run across” the

surface of the water (Cornell Lab of Ornithology, 2023).

5. Yellow Warbler (Setophaga petechia): a subtype of the wood warbler family, the yellow warbler is signified by its mostly yellow plumage, with a few stripes of chestnut color on the breast for males and overall yellow for females (Cornell Lab of Ornithology, 2023).

6. Cactus wren (Campylorhynchus brunneicapillus): A type of wren found in North American desert environments, from southwestern US to Mexico, signified by deep brown spots throughout its body. Its population is facing a decline due to rapid urbanization destroying its habitat (Cornell Lab of Ornithology, 2023).

7. Indigo Bunting (Passerina cyanea): A type of songbird found throughout eastern North America. Breeding males are signified by a bright blue color and females are signified by a brownish color. It is worth noting that non-breeding males have a blue and brown plumage. For identification purposes, the indigo buntings in this dataset are all breeding males (National Audubon Society, 2023).

8. Eastern Towhee (Pipilo erythrophthalmus): an eastern songbird that is relative to spotted towhee found throughout the west. Males have black back, rufous sides, and white belly, while females have brown back, rufous sides and white belly (Cornell Lab of Ornithology, 2023).

9. California Gull (Larus californicus): a type of seagull found through the western US and Mexico. Not to be confused with Herring gulls or Western gulls since they have yellow legs instead of pink and have dark eyes (National Audubon Society, 2023).

10. Ruby Throated Hummingbird (Archilochus colubris): The only hummingbird species that is found east of the Great Plains. They are excellent flyers and can flap their wings more than 50 times per second (National Audubon Society, 2023).

METHOD

Data Source

The source of the data used in this project is Caltech-UCSD birds 200, which contains images of 11788 images of 200 common bird species in North America taken in 2011 (Caltech, 2011).

Data Preprocessing

For the sake of simplicity, we decided to limit the classification categories to 10 instead of 200. Each bird category consists of 60 different images. To increase the size of the dataset, we augmented the number of images in each category to 120 by flipping each image sideways. This is because the original data sample is too small to perform adequately, and the new data sample had a significant improvement. However, we realized that there is still room for improvement for data diversity. As a result, we further augmented the number of images in each category to 240 by flipping each image upside down, which improved the performance even more. The training and test dataset are split with the ratio of 80:20 ratio, respectively. The random state is set to an arbitrary seed 100 to ensure that the train set and test set are consistently split. The training set is used to train the data, and the test set is used to evaluate the same model's accuracy in another random sample.

Models Used

This project utilizes the Convolutional Neural Network. Convolutional Neural Networks are a type of computational algorithm that has a similar structure to interconnected human neurons. The neural network consists of multiple layers, each layer filled with a certain number of nodes. Each node has a unique activation function and parameter associated with it. The neural network algorithm aims to find the optimal value of parameters that minimizes the loss function, which is a measure of error of the classification of the test set (A. Ilesanmi & T. Ilesanmi, 2021). Convolutional Neural networks consist of two types of layers: convolutional and dense, the former used to process 2d images, and the latter used to process 1d tensors after flattening (Mishra, 2020).

The Structure of the Model

The final version of the Convolutional Neural Network uses the Adam optimizer, the categorical cross entropy loss function, and consists of:

- One input layer
- One convolutional layer with the activation "ReLU"
- One 2d pooling layer
- One flattening layer
- Two Dense layers with ReLU as the activation function
- One output Dense layer with 10 nodes and softmax as the activation function

RESULTS

Tables 1 to 8 below show the metrics of each version of the model using holdout validation. The eighth model performed the best. The metrics of each version improved from the previous one. The validation accuracy of the best-performing model (i.e. the eighth) was 75%. The macro average recall and the macro average F1-score was 75% as well, while the macro average precision was 76%.

Overall, the bird species that was the most accurately identified was #3(Western Grebe). This is likely because of its unique shape as a member of the order Podicipediformes. Bird #0(American Crow), #2(Vermilion Flycatcher), and #4(Yellow Warbler) also were well-identified, likely because of their distinctive color. Though the performance was impressive, the model was more mediocre in identifying birds #1(blue jay) and #7(eastern towhee). This is likely because of these species' mixed colors, causing the model to confuse them with similar-looking species, such as confusing blue jays with indigo buntings.

The first version of the model, i.e., Version 1, consists of 1 convolutional layer without applying an activation function. It also includes 1 flattening layer, and 1 output layer. Table 1 below shows the performance of version 1.

Table 1

Classification Report of Version 1

	Precision	Recall	F1-Score
American Crow	0.33	0.33	0.33
Blue Jay	0.23	0.31	0.26
Vermilion Flycatcher	0.95	0.95	0.95
Western Grebe	0.60	0.09	0.16
Yellow Warbler	0.50	0.32	0.39
Cactus Wren	0.12	0.50	0.19

Indigo Bunting	0.29	0.50	0.37
Eastern Towhee	0.00	0.00	0.00
California Gull	0.71	0.18	0.29
Ruby-Throated Hummingbird	0.57	0.38	0.46
Micro Average	0.33	0.33	0.33
Macro Average	0.43	0.36	0.34
Weighted Average	0.44	0.33	0.32
Samples Average	0.33	0.33	0.33

For version 2, an activation function of ReLU was added to the convolutional layer in the model. Table 2 below shows the performance of version 2.

Table 2

Classification Report of Model 2

	Precision	Recall	F1-Score
American Crow	0.74	0.83	0.78
Blue Jay	0.39	0.38	0.39
Vermilion Flycatcher	0.95	0.95	0.95
Western Grebe	0.67	0.69	0.68
Yellow Warbler	0.90	0.86	0.88
Cactus Wren	0.44	0.50	0.47
Indigo Bunting	0.56	0.62	0.59
Eastern Towhee	0.62	0.21	0.31
California Gull	0.51	0.64	0.57
Ruby-Throated Hummingbird	0.61	0.67	0.64
Micro Average	0.63	0.63	0.63
Macro Average	0.64	0.64	0.63
Weighted Average	0.63	0.63	0.62
Samples Average	0.63	0.63	0.63

For version 3, a dense layer with no activation function before the output layer was added. Table 3 below shows the performance of model version 3.

Table 3

Classification Report of Version 3

	Precision	Recall	F1-Score
American Crow	0.86	0.79	0.83
Blue Jay	0.53	0.34	0.42
Vermilion Flycatcher	1.00	1.00	1.00
Western Grebe	0.68	0.72	0.70
Yellow Warbler	0.95	0.82	0.88
Cactus Wren	0.26	0.31	0.20
Indigo Bunting	0.67	0.75	0.71
Eastern Towhee	0.48	0.42	0.44
California Gull	0.47	0.57	0.52
Ruby-Throated Hummingbird	0.60	0.71	0.65
Micro Average	0.64	0.64	0.64
Macro Average	0.65	0.64	0.64
Weighted Average	0.65	0.64	0.64

	Precision	Recall	F1-Score
Samples Average	0.64	0.64	0.64

For version 4, another dense layer with leaky ReLU as the activation function was added. Table 4 below shows the performance of model version 4.

Table 4

Classification Report of Version 4

	Precision	Recall	F1-Score
American Crow	0.79	0.79	0.79
Blue Jay	0.67	0.34	0.45
Vermilion Flycatcher	0.87	1.00	0.93
Western Grebe	0.85	0.69	0.76
Yellow Warbler	1.00	0.77	0.87
Cactus Wren	0.56	0.62	0.59
Indigo Bunting	0.52	0.71	0.60
Eastern Towhee	0.61	0.46	0.52
California Gull	0.55	0.79	0.65
Ruby-Throated Hummingbird	0.69	0.86	0.77
Micro Average	0.69	0.69	0.69
Macro Average	0.71	0.70	0.69
Weighted Average	0.71	0.69	0.69
Samples Average	0.69	0.69	0.69

For version 5, another dense layer with leaky ReLU as the activation function was added to the model. Table 5 below shows the performance of model version 5.

Table 5

Classification Report of Version 5

	Precision	Recall	F1-Score
American Crow	0.78	0.75	0.77
Blue Jay	0.63	0.41	0.50
Vermilion Flycatcher	0.78	0.90	0.84
Western Grebe	0.85	0.88	0.86
Yellow Warbler	0.94	0.77	0.85
Cactus Wren	0.61	0.69	0.65
Indigo Bunting	0.58	0.75	0.65
Eastern Towhee	0.47	0.33	0.39
California Gull	0.61	0.79	0.69
Ruby-Throated Hummingbird	0.73	0.76	0.74
Micro Average	0.70	0.70	0.70
Macro Average	0.70	0.70	0.69
Weighted Average	0.70	0.70	0.69
Samples Average	0.70	0.70	0.70

Although version 5 was already achieving impressive performance, we realized that the data diversity in the original sample can still be improved. Thus, we augmented the data sample once more by flipping each image upside down, so each bird now has 240 images. Table 6 below shows the performance of model version 6.

Table 6

Classification Report of Version 6

	Precision	Recall	F1-Score
American Crow	0.77	0.85	0.81
Blue Jay	0.70	0.40	0.51
Vermilion Flycatcher	0.84	0.76	0.80
Western Grebe	0.77	0.85	0.81
Yellow Warbler	0.87	0.76	0.81
Cactus Wren	0.48	0.73	0.58
Indigo Bunting	0.59	0.80	0.68
Eastern Towhee	0.42	0.27	0.33
California Gull	0.45	0.60	0.51
Ruby-Throated Hummingbird	0.75	0.65	0.70
Micro Average	0.67	0.67	0.67
Macro Average	0.67	0.67	0.65
Weighted Average	0.68	0.67	0.66
Samples Average	0.67	0.67	0.67

After augmenting the image data once more, we realized that the performance fell a bit. To adjust for this change in version 7, we made a few adjustments to version 6, including adjusting the pooling layer's filter size and changing the first dense layer's activation function to ReLU. This improved the performance significantly. Table 7 below shows the performance of model version 7.

Table 7

Classification Report of Version 7

	Precision	Recall	F1-Score
American Crow	0.79	0.88	0.83
Blue Jay	0.66	0.56	0.61
Vermilion Flycatcher	0.91	0.74	0.82
Western Grebe	0.81	0.83	0.82
Yellow Warbler	0.88	0.83	0.86
Cactus Wren	0.46	0.79	0.58
Indigo Bunting	0.69	0.85	0.76
Eastern Towhee	0.65	0.49	0.56
California Gull	0.63	0.70	0.67
Ruby-Throated Hummingbird	0.82	0.60	0.69
Micro Average	0.73	0.73	0.73
Macro Average	0.73	0.73	0.72
Weighted Average	0.74	0.73	0.73
Samples Average	0.73	0.73	0.73

For version 8, the final and best performing version so far, we made some final adjustments to further improve the model's performance, such as adjusting the number of nodes and adding another dense layer with ReLU as the activation function. Table 8 below shows the performance of model version 8.

Table 8

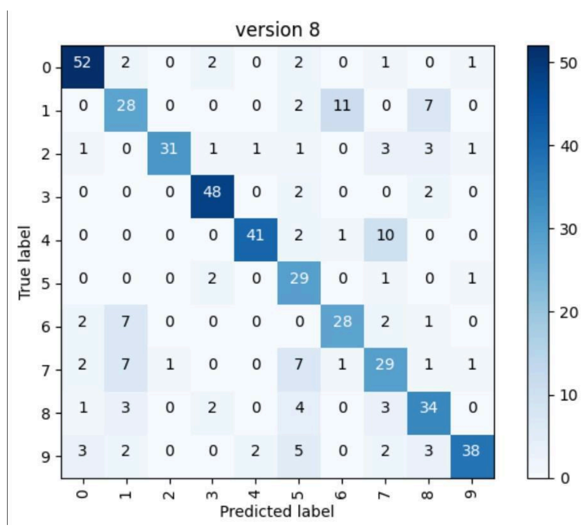
Classification Report of Version 8

	Precision	Recall	F1-Score
American Crow	0.85	0.87	0.86
Blue Jay	0.57	0.58	0.58
Vermilion Flycatcher	0.97	0.74	0.84
Western Grebe	0.87	0.92	0.90
Yellow Warbler	0.93	0.76	0.84
Cactus Wren	0.54	0.88	0.67
Indigo Bunting	0.68	0.70	0.69
Eastern Towhee	0.57	0.59	0.58
California Gull	0.67	0.72	0.69
Ruby-Throated Hummingbird	0.90	0.69	0.78
Micro Average	0.75	0.75	0.75
Macro Average	0.76	0.75	0.75
Weighted Average	0.77	0.75	0.75
Samples Average	0.75	0.75	0.75

Another way to visualize the performance of the models is through a confusion matrix, with the grids symbolizing the true label and predicted label of an image. The ideal performance would align on the diagonal from the top-left corner to the bottom-right corner, symbolizing that the true labels and the predicted labels match each other. The confusion matrix below represents the model with the best performance, which is version 8. As shown in Figure 1 below, the model had a great performance most of the times, especially when identifying birds assigned the true labels #0(American Crow), #2(Vermilion Flycatcher), #3(Western Grebe), and #4(Yellow Warbler), achieving a robust F1-Score of 0.86, 0.84, 0.90 and 0.84, respectively. While the model can often identify birds assigned the true labels #1 (blue jay) and #7 (eastern towhee), the performance is more mediocre when compared to the other types of birds. This can be explained because it is possible to confuse these birds with other species that look similar, such as confusing #1(Blue Jay) with #6(Indigo Bunting) because they both have blue in their colors, and confusing #7(Eastern Towhee) with #8(California Gull) because they both have white in their colors.

Figure 1

Confusion Matrix of Model Version 8

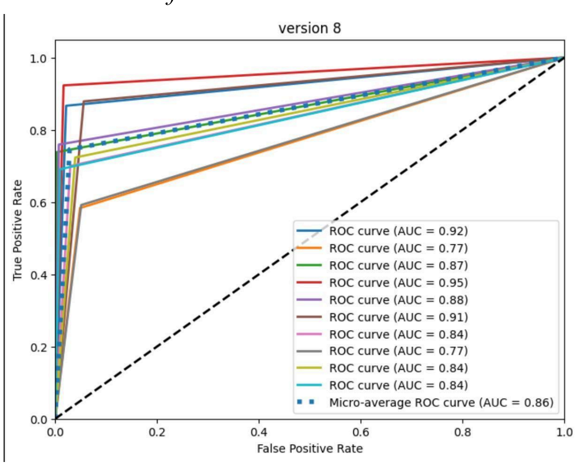


Another visualization method is to use a Receiver Operating Characteristic (ROC) curve, which is a graph of the true positive rate (TPR) as a function of the false positive rate (FPR) in the domain and range of [0,1]. The TPR, which is high in ideal cases, is calculated as (True positive) / (True Positives + False Negatives), and the FPR, which is low in ideal cases is measured as (False Positives) / (False Positives + True Negatives). This means that in ideal cases, the curve would be as close to the top left corner as possible, signifying that there are only true positives and no false positives. A method to measure how accurate the model performs is looking at the area under the curve (AUC) of an ROC curve. Models that have better performance have an AUC closer to 1.

Figure 2 below shows the ROC curve of version 8. The black line is the diagonal of the graph, representing the curve if the decision is made entirely randomly. As shown in Figure 2, all curves are far away from the diagonal and close to the top-left corner, meaning that they performed fairly well. The model performs exceptionally well at identifying American Crow (represented by the dark blue curve) and Western Grebe (represented by the red curve), achieving an exceptional AUC of 0.92 and 0.95, respectively. The ROC curve of Blue Jay (represented by the orange curve) and Eastern Towhee (represented by the grey curve) are close to the black diagonal, meaning that they performed relatively mediocre compared to the others.

Figure 2

ROC Curves of Version 8



DISCUSSION

When the model makes random guesses, predicted accuracy is 10%. After many adjustments to the model, the accuracy increased to 75%, which is a substantial increase in performance. This increase in accuracy illustrates that it is a reliable method to classify the images in the dataset. Though initially we faced some limitations, we managed to tackle them all through a variety of methods.

When initially processing the data, we faced some limitations, such as data diversity. However, we addressed it through data augmentation: artificially increasing the data amount without adding new data into the dataset, which is often done when data is not readily available (Chlap, Min, Vandenberg, Dowling, Holloway, & Haworth, 2021). We managed to address this problem through data augmentation by flipping the image sideways and appending them to the data files. This significantly increased accuracy. However, after revising the data we realized that there is still room for improvement, so we augmented the dataset once more by flipping all the images upside down, significantly increasing the data size to 4 times the original size. As shown in figure 3, 4, and 5 below, there is a visible increase in performance of the model each time the data gets augmented as the ROC curves shift towards the top-left corner, meaning a higher TPR and a lower FPR.

Figure 3

ROC Curves of Version 8 Before Image Augmentation

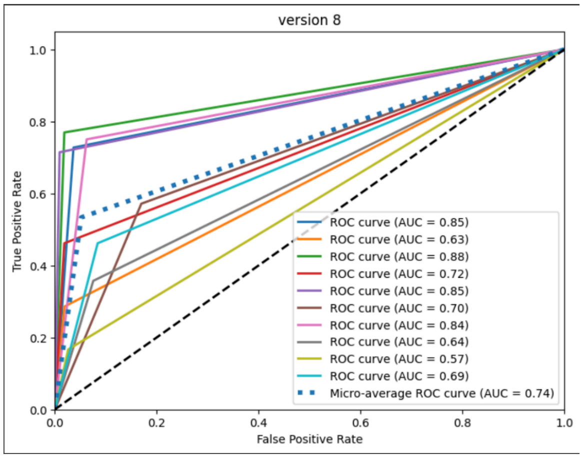


Figure 4

ROC Curves of Version 8 after Augmenting the Dataset to Twice its Original Size

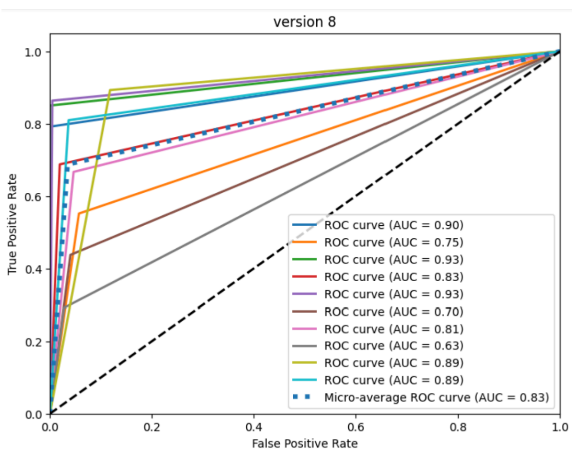
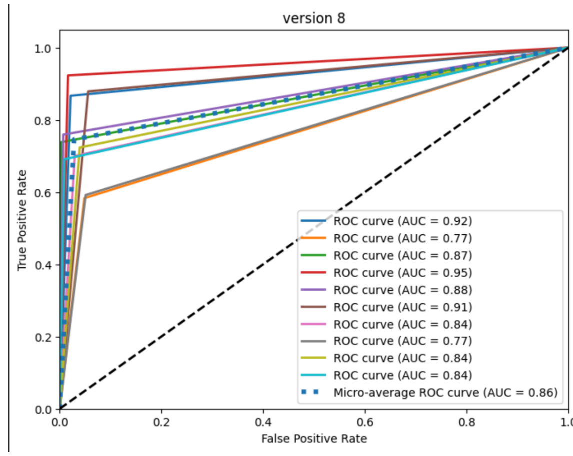


Figure 5

ROC Curves of version 8 after augmenting the dataset to four times its original size



Another limitation is the hardware requirements. To train the data, large storage is required. The most developed layout of seven layers has shown to take a large amount of computing resources. However, we also managed to tackle this problem by using Google Colaboratory. Shifting the project online allows us to utilize Google Colaboratory's high computing power, allowing us to build a more robust model without worrying about the program crashing.

CONCLUSION

This research project aims to develop a convolutional neural network that serves as an efficient way to classify birds based on its images. Based on further research, it can be concluded that convolutional neural networks have potential in achieving impressive results, and they can also adapt to handle the complexities inherent in bird image classification. In conclusion, the model did a decent job in classifying 10 common bird species, with accuracy at 0.75, macro average precision at 0.76, and macro average recall at 0.75 with 50 training epochs and an 80:20 train test split. This is significant since it is a potential direction where future improvements can be conducted such that the model will be able to identify a wider range of birds (with some tweaking and providing enough data) so it can serve as an alternative to human powered identification. This can potentially bring a new perspective in ornithology and help amateur birders better understand different bird species. Convolutional neural networks can revolutionize the field of avian identification, offering a cutting-edge solution that not only showcases its prowess in recognizing a diverse range of bird species.

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