Proceedings of the Second International Conference on Automation, Computing and Renewable Systems (ICACRS-2023)
IEEE Xplore Part Number: CFP23CB5-ART; ISBN: 979-8-3503-4023-5

An Eagle-Eye Vision: Advancements in Avian Species Classification

P. Kanaga Priya[1]
Department of Computer Science and Engineering,
KPR Institute of Engineering and Technology,
Coimbatore, India
kanagapriyacse@gmail.com

M.S. Vinu[2]
Department of Computer Science and Engineering,
Nehru Institute of Engineering and Technology,
Coimbatore, India
vinuja@gmail.com

PrasannaBlessy M[3]
Department of Computer Science and Engineering,
RVS Technical Campus,
Coimbatore, India.
blessypaul90@gmail.com

P. Kirupa[4]
Department of Computer Science and Engineering,
SNS College of Engineering,
Coimbatore, India
kirupa0705@gmail.com

R. Gayathri[5]
Department of Electronics and Communication Engineering,
Coimbatore Institute of Engineering and Technology,
Coimbatore, India
gayathriyaso@gmail.com

N. Selvakumar[6]
Department of Computer Science and Engineering,
SNS College of Technology,
Coimbatore, India
selvaa618@gmail.com

2023 2nd International Conference on Automation, Computing and Renewable Systems (ICACRS) | 979-8-3503-4023-5/23/$31.00 ©2023 IEEE | DOI: 10.1109/ICACRS58579.2023.10404897

***Abstract*— Avian species taxonomy is an important activity in the domain of ornithology, wildlife preservation, and ecological research. Convolutional Neural Networks (CNNs) a widely used tool for automating categorization jobs in recent years. This abstract provides an overview of applying Eagle-Eye CNN to the classification of bird species. The methodology originates with image pre-processing, comprising scaling, normalization, and augmentation, to strengthen model resilience. Subsequently, the feature extraction is accomplished inside the CNN architecture layers. Moreover, the use of transfer learning harnesses the proposed CNN model, fine-tuned for the particular job of the Eagle-Eye vision engine for bird species classification. The proposed pre-trained model can also be used for other classification tasks. This technique attains a remarkable accuracy of 89% due to its large dataset and holds potential for further applications across avian taxonomy. In summary, CNNs offer an effective avenue for automated bird or avian classification, permitting more efficient and exact bird behavior study thus enhancing avian conservation attempts.**

Keywords*— *Avian classification, Bird, Convolutional Neural Network, Eagle-Eye vision engine, Accuracy.

I. INTRODUCTION

In the area of animal protection, ornithology, and ecological research, the correct and efficient taxonomy of bird species bears paramount importance. The thorough identification of avian species is vital for tracking migration patterns, identifying habitat preferences, monitoring population dynamics, and estimating the impacts of environmental changes on bird populations. Traditionally, ornithologists and researchers have depended on manual identification methods, often based on visual cues, bird cries, and physical traits, which can be time-consuming and labor-intensive. However, the introduction of contemporary technology and the rapid growth of imaging data have opened new frontiers in the field of bird species classification. The demand for automated and precise classification technologies has never been more pronounced. Deep learning, a subfield of artificial intelligence, has emerged as a disruptive force in this regard.

Convolutional Neural Networks (CNNs), a special family of deep learning models, have exhibited amazing skills in image identification and classification applications. Their ability to understand complicated patterns and features from enormous volumes of visual data has made them a useful tool for automatic bird species classification. This article addresses the integration of deep learning techniques, notably CNNs, into the realm of bird species classification, offering light on their value and efficiency. This study includes an in-depth investigation into the application of CNNs for bird species classification, presenting an overview of the methods, from picture pre-processing to feature extraction and transfer learning. The suggested strategy not only boosts the accuracy of bird species identification but also streamlines the process, decreasing the reliance on manual methods and enabling a greater range of applications in bird behavior studies, conservation, and ecological studies. The achieved accuracy highlights the potential of CNNs in revolutionizing the field of avian species classification and the opportunity they bring for more precise and efficient research and conservation activities.

II. LITERATURE REVIEW

Bird species identification is vital, and photos and audio have been employed for this purpose. However, background noise and similar bird forms make it challenging. Higher accuracy features have been extracted from photos using Deep Learning (DL) models. To categorize bird species, recent methods utilize spatial pyramid pooling and transfer learning, while Mask-CNN solves a few shot classification issues effectively. This study discusses DL algorithms for recognizing bird species, analyses their performance, and stresses future improvements for increased efficiency [1]. The increasing threat of extinction of animal and avian species is a major worry for human civilization. To preserve the co-existence of all species, conservation measures are being implemented. This study proposes a system for identifying birds in images using convolutional neural networks. To categorize and identify bird photos, four transfer learning-based architectures were used with 400 different bird species' 58388 photos to train the models. With a significant loss of 0.8835, Resnet152V2 had the highest accuracy of any model, at 95.45%. DenseNet201 experienced a decreased loss of 0.6854 despite having an accuracy of 95.05%. The findings imply that DenseNet201 could be applied to the classification of real-world bird images. However, the models can be fine-tuned for higher accuracy and recognition. This could require increasing the number of epochs or unfrozen layers of the transfer learning models [2].

Because they convert pollutants into nutrients and help to maintain a stable climate, birds are vital to ecosystems. It might be difficult to distinguish between different bird species from audio recordings. Sequential aggregation techniques and ensemble fusion models enhance multi-label bird call classification. The 2-Classifier model outperforms baseline and chromagram-based models, with an F1-score of 0.60. The experimental evaluation uses the Xeno-canto bird sound database [3]. Animal behavior and mobility in both natural settings and experimental settings have been examined through manual behavioral observations. These observations take a lot of time, and work, and are prone to mistakes. Open-source software techniques derived from automated behavioral analysis are applicable to other vertebrates such as birds. Pose estimation data for pigeon behaviors can be analyzed to create supervised machine-learning predictive classifiers using open-source tools. Seven different behaviors can be trained to yield an F1 score of 0.874 using various machine learning and deep learning architectures. The technology is expected to assist scientists in extracting precise behavioral data under a variety of experimental situations and is interface-compatible with existing machine learning architectures [5]. Because they have such diverse appearances, bird species are getting harder to recognize and characterize. The Caltech-UCSD Birds 200 dataset was utilized by researchers for training and validation in order to enhance discrimination. Grayscale representations and a rating table were created using tensor flow and deep convolution neural networks. With Linux and the Tensorflow framework, the system achieved an 89% accuracy rate in bird identification, demonstrating the potential of this technology in identifying different species of birds [6].

To enhance the identification and classification of bird species, scientists employed the Caltech-UCSD Birds 200 dataset. Grayscale representations and rating tables were produced using Tensor Flow and Deep Convolution Neural Networks. The Tensorflow framework and Linux were used to obtain an accuracy of 89% in bird recognition. Multiple-width frequency delta data augmentation is almost state-of-the-art and has an advantage over raw spectral data when computer resources are scarce, even though it cannot improve classification accuracy. Researchers studying picture segmentation and defect-recognition may find this work useful [7]. Birds' ability to survive is becoming more and more threatened by the declining ecological environment. An automatic system for recognizing bird images is required in order to safeguard these species. This study evaluates the effectiveness of deep learning and conventional machine learning models for picture identification, as well as the usefulness of transfer learning in the domain. Convolutional neural networks, transfer learning-based convolutional neural networks, and conventional machine learning algorithms were the three types of classifiers that were built. Experiments on the Kaggle-180-birds dataset revealed statistically significant variations in the categorization effect. The findings demonstrated that when bird species rise, deep learning outperforms conventional machine learning methods in terms of effectiveness. When sample data is small, transfer learning can also increase classification accuracy [9]. Hence the various studies show the importance of accurate bird species classification with respect to various procedures.

III. PROPOSED SYSTEM

A. Proposed Eagle-Eye vision system and its overall process

The proposed system describes a system for classifying different bird species from input photos using the DCNN (Deep Convolutional Neural Network) architecture. One important pre-processing step included in the suggested method is the scaling, normalization, and augmentation of the input bird photos. By ensuring that all images have consistent dimensions, resizing makes them appropriate for use with the CNN model. The model can reliably analyze photos thanks to this standardization. By transforming the pixel data, normalization guarantees a zero mean and unit variance. In addition to preventing overfitting to the training set, this reduces the effect of color fluctuations and lighting on the model's performance.

Additionally, augmentation is utilized to produce more training data by transforming the original bird photos in a variety of ways. This strategy expands the train dataset, which improves the resilience and generalization abilities of the CNN model. Through the exposure of the model to different avian data variant samples, augmentation also lowers the danger of overfitting. Together, these pre-processing methods help the model become more accurate, resilient, and generalizable, which improves its ability to classify different bird species especially when it comes to data that has never been seen before. Feature extraction and classification are still essential components of the Convolutional Neural Network (CNN) model for classifying bird species. Finding distinctive qualities in the input bird photos that are essential for precise classification is known as feature extraction. In this approach, CNN algorithms are crucial because they examine the image's structures and patterns. To do this, pooling layers that reduce the dimensionality of the feature maps and many convolutional layers that recognize distinctive features and patterns are utilized. This condenses the relevant attributes needed for classification.

Eagle-Eye vision deep learning techniques are utilized in the classification step to identify the species of birds after feature extraction. Using the feature maps as input, fully linked layers infer the relationship between the features and the output labels. These layers anticipate the most likely species by generating probabilities for each bird species using a Rectified Linear Unit (ReLU) activation function. The CNN model is able to identify distinctive properties that set one bird species apart from another because of this integrated feature extraction and classification procedure. This method outperforms traditional algorithms and routinely achieves high levels of accuracy in the classification of bird species. Eagle-Eye vision models automate the classification process, saving researchers and conservationists time and effort while offering valuable insights into the identity and behavior of many bird species. To correctly forecast bird species, a new Eagle-Eye vision prediction engine was developed and implemented, as illustrated in Fig. 1, which contained the tasks and actions necessary to accomplish this goal.

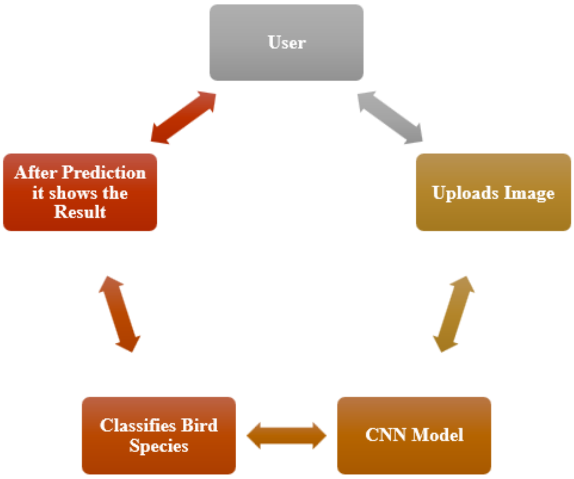

Fig. 1. Overall Process

B. The architecture Eagle-Eye vision prediction engine

Getting a relevant dataset that is specifically designed for bird photos is the first stage in developing a neural network for classifying bird species. To enable efficient model training and assessment, these data samples are then divided into a training set and a test set. The neural network is then trained with architectural layers, and the training images which are primarily pictures of birds—are added to the model and put through the fitting procedure. A thorough testing process is carried out to evaluate the model's performance as it is being trained. It is crucial to confirm that the model can correctly categorize various bird species. It is wise to store the model and any related dependencies for later usage after it has been suitably trained and evaluated. Following a thorough study, the work proposed an Eagle-Eye vision prediction engine, which is part of the deep learning CNN family of methods, and is utilized to extract important information from bird photos. CNNs are remarkably adept at managing large datasets with a multitude of picture attributes. They do this by dividing up large feature sets into two-dimensional representations and connecting these representations to the outputs that correspond to them. These multilayer CNNs use input datasets of bird images to dynamically learn new features under the guidance of a supervised learning framework. Eagle-Eye vision CNN uses a standardized design to categorize these properties into discrete groups, as seen in Fig. 2. This method plays a key role in automating the classification of various bird species and provides insightful information into the field of avian classification.

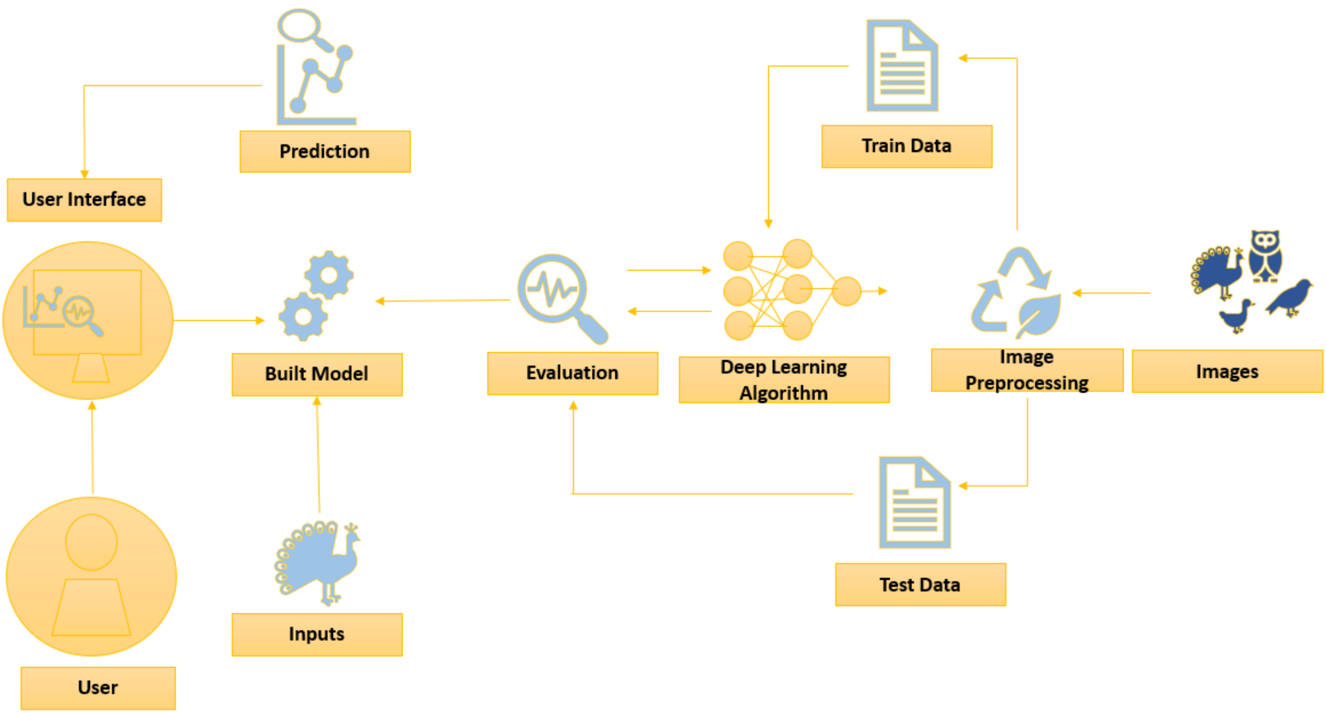

Fig. 2. Eagle-Eye vision prediction engine

C. Description of data samples

To develop an Eagle-Eye vision CNN network is able to identify diseases in avian species, the Dataset (BIRDS 525 SPECIES- IMAGE CLASSIFICATION) from Kaggle which includes ten new species has been added to the dataset in comparison to the previous edition. Furthermore, the duplicate or almost duplicate photos from the dataset by utilizing a dataset analysis tool. This guarantees that the training, test, and validation datasets don't leak information. Additionally, low-quality, faulty photos were eliminated. Hence worked on a clean dataset. It contains a collection of 525 bird species data. There are 2625 test images (five images per species), 2625 validation images (five images per species), and 84635 training images. There is just one bird per picture in this extremely high-quality dataset, and the bird usually occupies at least half of the image's pixels. Every image is a 224 by 224 x 3-colour JPG file. A train set, test set, and validation set are all part of the data set. There are 525 subdirectories in each set, one for every species of bird. If you generate the train, test, and valid data generators using the Keras ImageDataGenerator, the data structure is convenient. Below Fig. 3 shows the distribution of the dataset and Fig. 4. Shows the data samples of the dataset.

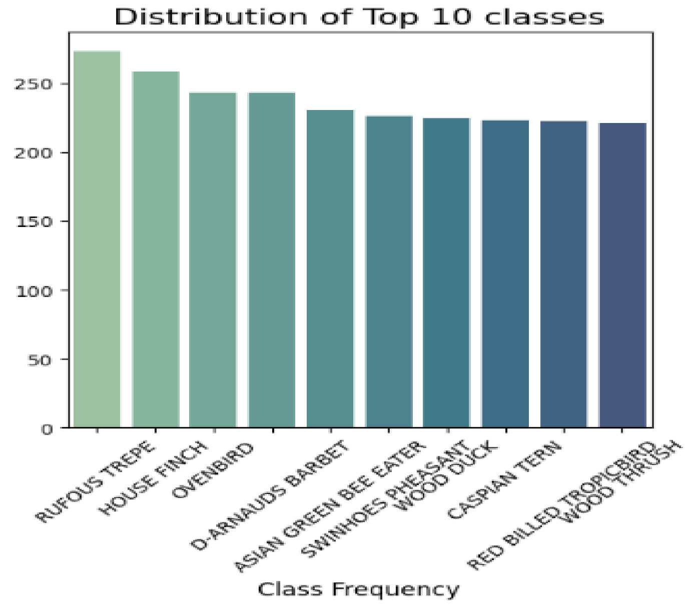

Fig. 3. Distribution of Dataset

Fig. 4. Data samples of the dataset

IV. METHODOLOGY

A. The proposed model training and its implementation

Data samples are methodically gathered at the beginning of the process to lay the groundwork for later phases. Following collection, these data samples go through a crucial pre-processing step that makes sure they are in a format that is appropriate for model testing and training. The picture augmentation technique is used after pre-processing. By producing several versions of every image in the dataset, this method successfully diversifies the dataset and increases the suggested model's resistance to changes in the input data. Several factors, including dense convolution, max pooling, batch size, and flattening are taken into consideration while the model is trained and evaluated using the prepared dataset. The convolution layer incorporates many activation functions, including dense, shape, matrix, and ReLU, to extract relevant characteristics from the images. More dense layers that apply the ReLU activation function at each level can be added to the hidden layers to help in feature learning and representation. After that, test data is used to thoroughly assess the model's performance, as shown in Fig. 5. The model is retained for use and deployment at a later time after it satisfies the required standards for accuracy and generalization. Finally, the saved model is put to use via a web-based interface that makes use of a Flask file. This enables users to effortlessly utilize the model's categorization capabilities and make predictions. The accessibility and usefulness of the model in practical situations are improved by this technique it is easy to apply.

Fig. 5. Eagle-Eye CNN model implementation

Users can upload photographs for in-depth examination through the user interface. After an image is uploaded, it is put through a rigorous pipeline of processing using a model that has already been trained. The user interface presents the results in a timely manner. This application's main goal is to correctly identify avian species from the provided photographs. In order to accomplish this, the model uses the popular optimization method known as the Adam optimizer to determine the corresponding loss, hence improving the model's accuracy and predictive power. The application's fundamental model uses sophisticated deep learning methods to make use of neural networks' ability to interpret complex patterns and characteristics in images. An easy-to-use Flask-based web application incorporates this concept smoothly, guaranteeing a simple and straightforward user experience. Although it can only recognize a large avian species at this time, this model's capacity to recognize bird faces even from a single image is a noteworthy benefit. In order to serve a larger audience, future efforts aim to broaden the model's coverage by including a wider range of avian species. Fig. 6 shows the output predictions of the Eagle-Eye vision prediction engine, which highlights the recognized avian species and gives viewers useful information to help them identify different kinds of birds.

Fig. 6. Prediction of Early-Eye Vision Engine

B. *Accuracy*

The proposed Early-Eye vision engine is specifically designed for bird species identification, a large dataset consisting of 84,635 samples each representing one of the 525 different bird species is utilized. Important criteria like the number of training epochs, the loss function, and the model's accuracy on test data are used to evaluate this model. The model's prediction performance is characterized by remarkable precision, as seen in Fig. 7. The model performs admirably, achieving a training loss of 1.0879, training accuracy of 0.9939, validation loss of 1.2749 and validation accuracy of 0.8800, on the training and validation datasets. This highlights the model's competence in identifying avian species and demonstrates its capacity to reliably and efficiently categorize a variety of bird species on a large dataset.

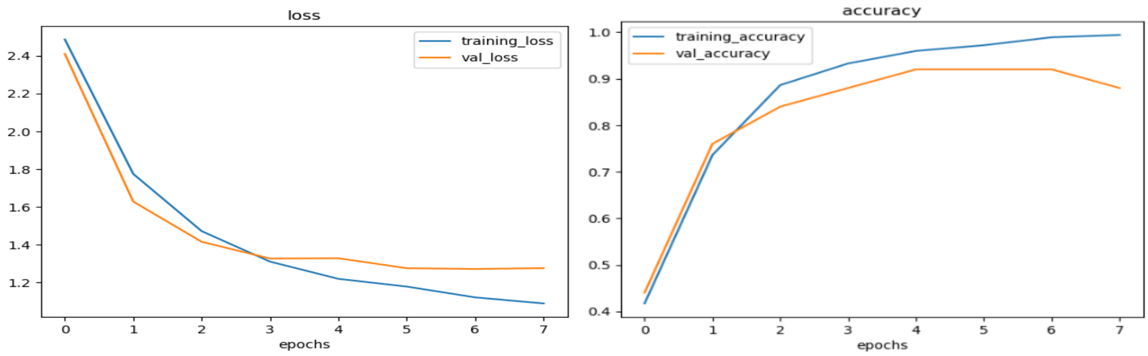

Fig. 7. Early-Eye vision engine model loss and accuracy for avian species

V. CONCLUSION

The main goal was to develop a reliable technique for classifying bird species accurately from input photos, especially in situations with cluttered and complex backgrounds. The used Eagle-Eye vision deep neural network that has been specifically trained to classify bird species to achieve this. Our experimental results clearly showed that our proposed method is superior to current methods, with an outstanding accuracy rate for bird species classification on a comparatively large dataset. Further, the accuracy needs to be improved by applying the fine-tuned parameters. Beyond these achievements, our research continues. In this study, an application is developed that uses artificial intelligence and computer vision techniques to forecast the movements of birds. The goal is to use a variety of datasets to train the program and assess its performance with real-time photos taken by cameras in a range of settings, such as residential areas and forests. With the goal of improving the application's accuracy in categorizing bird photos in real-world scenarios, this testing could potentially save lives by alerting pertinent parties to ecologically significant circumstances.

Hence for many ecological and conservation initiatives, the categorization and identification of bird species are crucial. Comprehending the diversity of birds helps maintain ecosystems, stabilizes the temperature, and lessens the negative effects of toxins on the environment. For the purpose of tracking population shifts, evaluating the health of the ecosystem, and directing conservation efforts, accurate bird species taxonomy is essential. Additionally, studies on the behaviour and mobility of birds as well as the creation of automated recognition systems provide researchers with useful tools to collect accurate behavioural data, advancing our knowledge of bird species and their ecological roles. The classification of bird species is important for protecting these species and their habitats from environmental challenges, as well as for improving our understanding of biodiversity.

REFERENCES

[1] B. Sivaranjani and S. Karpagavalli, "A Survey and Analysis of Deep Learning Techniques for Bird Species Classification," 2023 International Conference on Sustainable Computing and Smart Systems (ICSCSS), Coimbatore, India, 2023, pp. 215-221, doi: 10.1109/ICSCSS57650.2023.10169573.

[2] A. Manna, N. Upasani, S. Jadhav, R. Mane, R. Chaudhari, and V. Chatre, "Bird Image Classification using Convolutional Neural Network Transfer Learning Architectures," International Journal of Advanced Computer Science and Applications, vol. 14, no. 3, 2023.

[3] A. Noumida, R. Mukund, N. M. Nair and R. Rajan, "Multi-label Bird Species Classification Using Ensemble of Pre-trained Networks," 2023 International Conference on Intelligent Systems for Communication, IoT and Security (ICISCoIS), Coimbatore, India, 2023, pp. 644-649, doi: 10.1109/ICISCoIS56541.2023.10100519.

[4] N. Wittek, K. Wittek, C. Keibel, and O. Güntürkün, "Supervised machine learning aided behavior classification in pigeons," Behavior Research Methods, vol. 55, no. 4, pp. 1624-1640, 2023.

[5] S. Juliet, "Image-Based Bird Species Identification Using Machine Learning," in 2023 9th International Conference on Advanced Computing and Communication Systems (ICACCS), vol. 1, March 2023, pp. 1963-1968. IEEE.

[6] P. Anusha and K. ManiSai, "Bird species classification using deep learning," in 2022 International Conference on Intelligent Controller and Computing for Smart Power (ICICCSP), July 2022, pp. 1-5. IEEE.

[7] B. K. Rai, S. Sharma, G. Kumar, and K. Kishor, "Recognition of Different Bird Category Using Image Processing," International Journal of Online & Biomedical Engineering, vol. 18, no. 7, 2022.

[8] A. Noumida and R. Rajan, "Multi-label bird species classification from audio recordings using attention framework," in Applied Acoustics, 2022, vol. 197, p. 108901.

[9] M. Alswaitti, L. Zihao, W. Alomoush, A. Alrosan, and K. Alissa, "Effective classification of birds' species based on transfer

learning," International Journal of Electrical and Computer Engineering (IJECE), 2022, vol. 12, no. 4, pp. 4172-4184.

[10] H. Wang, Y. Xu, Y. Yu, Y. Lin, and J. Ran, "An efficient model for a vast number of bird species identification based on acoustic features," in Animals, 2022, vol. 12, no. 18, p. 2434, IEEE.

[11] Y. P. Huang and H. Basanta, "Recognition of endemic bird species using deep learning models," 2021, IEEE Access, vol. 9, pp. 102975-102984.

[12] G. Gupta, M. Kshirsagar, M. Zhong, S. Gholami, and J. L. Ferres, "Comparing recurrent convolutional neural networks for large scale bird species classification," Scientific Reports, 2021, vol. 11, no. 1, p. 17085.

[13] P. Gavali and J. S. Banu, "Bird species identification using deep learning on GPU platform," in 2020 International Conference on Emerging Trends in Information Technology and Engineering (ic-ETITE), February 2020, pp. 1-6. IEEE.

[14] K. M. Ragib, R. T. Shithi, S. A. Haq, M. Hasan, K. M. Sakib, and T. Farah, "Pakhichini: Automatic bird species identification using deep learning," in 2020 Fourth World Conference on Smart Trends in Systems, Security, and Sustainability (WorldS4), July 2020, pp. 1-6. IEEE.

[15] S. Islam, S. I. A. Khan, M. M. Abedin, K. M. Habibullah, and A. K. Das, "Bird species classification from an image using VGG-16 network," in Proceedings of the 7th International Conference on Computer and Communications Management, July 2019, pp. 38-42.