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Deep Learning Based Bird Species Identification and Classification Using Images

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Abstract: In the natural realm, humans often consider bird-watching to be a captivating hobby. Worldwide, there are more than 9000 species of birds. Certain bird species are becoming progressively scarce, and even when encountered, accurately determining their classification can be challenging. Accurately identifying a bird species demands a profound understanding of ornithology, a field of knowledge that often surpasses the breadth of human expertise. Maintaining ecological balance and the preservation of biodiversity both depend on the recognition of different species of birds. Additionally, birds are useful in many other endeavors such as agriculture, the creation of landscapes, the development of coral reefs, etc. One of the most important tasks in ecology is the recognition and monitoring of birds of different kinds to evaluate changes in bird communities over time, patterns of migration, and population dynamics in order. Because there are parallels between intraclass and interclass variations of bird species, it can be exceedingly challenging to identify the species of birds in many situations. Convolutional Neural Networks, also known as CNNs, have recently enabled some cutting-edge image categorization algorithms to reach astounding results. This work suggested a skip connection-oriented neural network architecture to enhance feature extraction. The model was trained and tested for 525 species of birds with a total 28,927 training images (approximately 55 images per species),2,625 testing images, and 2,625 validation images (5 images per species in both). The accuracy of the suggested CNN model with skip connections was 92% as opposed to a CNN's 90%. The outstanding results of this work show that deep learning algorithms are capable of identifying birds in a variety of habitats. The accuracy of the suggested CNN model with skip connections was greater at 91.0 % than that of the state of art CNN model. Reaching a 92% accuracy rate in identifying bird species has important real-world applications that have a big impact on ecological research and conservation initiatives The high accuracy enables researchers to conduct comprehensive habitat assessments, identifying key areas that require conservation attention or restoration efforts.

Keywords: Bird species classification; Convolution Neural Network (CNN); Skip Connection; Deep learning.

1. Introduction

The biodiversity that surrounds us is crucial to civilization as a whole because it keeps ecosystems in proportion. One of the most vital resources is birds, which benefit humans in many ways such as pollination and defending crops from damaging pests that would otherwise kill them. Presently, identifying different species of birds is seen to be a difficult task that usually leads to confusion. It takes a lot of human labor to acquire and compile data on birds. A lot of people visit bird sanctuaries to observe the birds, but very few of them are aware of the differences between the various species and their characteristics. The increasing grasp of these species distinctions will lead to an increase in knowledge of birds, their ecosystems, and their biodiversity. The identification of birds with the naked eye is generally reliant on fundamental characteristics due to observer restrictions, such as location, distance, and equipment; suitable classification based on specific attributes is often found to be arduous. A challenge for ornithologists has been identifying different species of birds. The distribution, genetics, breeding climate and environmental effects of each bird must be known to identify it correctly. Researchers in the environmental field have become interested in deep learning methods such as convolutional neural networks, also called CNNs, over the last few years. In the study of ecology and research, artificial intelligence methods and procedures are used to accurately identify the species of organism, animal, or bird from images.

Correctly identifying a species is a crucial first step in preserving it, after that requires the right preservation methods. Due to its ability to extract intricate bird traits and make more accurate predictions, deep learning emerges as the optimal choice for automated bird species recognition. Deep learning excels in recognizing a bird's species through visual cues, video content, and sound recordings. The Convolutional Neural Network (CNN) was utilized in this [1] to categorize the bird species. A deep learning technique was presented for more accurate identification of several bird species from their sounds. The suggested approach blends coordinated attention and long short-term memory algorithms in this study [2]. Xeno Canto provided over 70,000 bird-call recordings from 264 different species of birds. The recommended network's mean average precision was found to be 77.43% in an evaluation exercise. The primary goal [3] is to create and assess an advanced framework for bird species identification, employing deep learning convolutional neural networks (DCNNs) to analyze audio spectrogram inputs. The creation of a system for classifying species of bird can assist officials in monitoring the birds in a certain area by keeping an eye on each kind of bird. Hence, this study proposes a method based on deep learning, trained on bird photos, to address this identification challenge.

1.1. Challenges in the accurate identification and classification of bird species.

A few major barriers to correctly identifying and classifying bird species. These difficulties are especially important in areas like wildlife protection, birding, and ornithology. These difficulties are shown in Figure 1. In order to overcome these difficulties, professionals in the field of bird image identification are working to create powerful machine-learning models, enhance the methods for gathering data and annotating it, and cooperate with ornithologists to guarantee precise species identification.

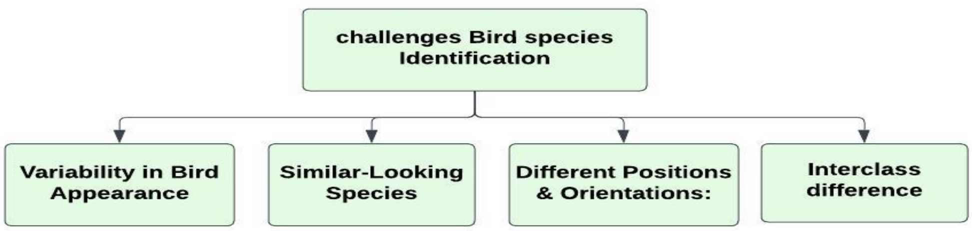

Figure 1. Challenges Bird species identification

1.1.1. Variability in Bird Appearance

Some birds come in the same shapes, colors, sizes. Accurate identification of some species may be challenging due to the presence of small, imperceptible variations.

1.1.2. Similar-Looking Species

Several bird species resemble one another. particularly amongst members of the same genus or family. It takes observation and expertise to tell these species apart from one another.

1.1.3. Different Positions & Orientations

Birds can be captured in different poses and orientations. It makes it a challenge to provide accurate output.

1.1.4. Interclass difference

Due to variables including age, gender, and geographic location, some bird species may exhibit significant intra-species variation, which can make classification more difficult.

1.2. Different Types of Birds Species

Several separate bird groups, each with special traits and adaptations, figure 2 lists several bird species categories.

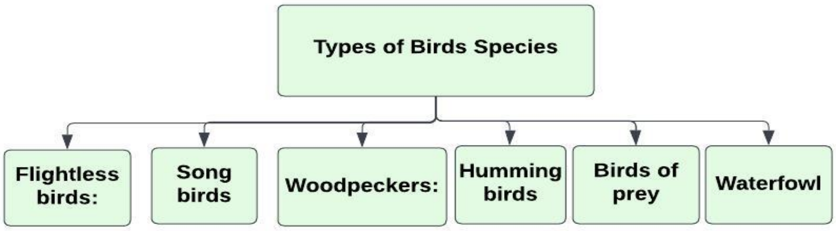

Figure 2. Types of Bird Species

1.2.1. Songbirds

The vocalizations of songbirds, which are frequently melodious, are well recognized. Compared to some of their other feathered relatives including thrushes, and orioles the songbirds are smaller.

1.2.2. Woodpeckers

Woodpeckers are an impressive group of birds. They can use their long and strong beaks for forage to insect that they beat against tree trunks.

1.2.3. Hummingbirds

Hummingbirds are amazing bird species distinguished by their diminutive stature, remarkable dexterity, and vivid feathers.

1.2.4. Birds of prey

Birds of prey have incredible eyesight which they use to hunt. Their beaks are strong and large which allows them to slice and tear apart food with ease.

1.2.5. Waterfowl

They have feathers that are so oily that they practically serve as a barrier to keep water from soaking them. Each toe has thick skin in between them that functions almost like a paddle for their feet, enabling them to swim effortlessly.

1.2.6 Flightless birds

Birds are well known for their ability to fly but some are not enjoying this luxury. For example: emperor penguin, ostrich.

Online sites has been deployed to gather the dataset for this work. For the classification, the CNN algorithm is employed. To get a good result, the model will be verified and trained on images.VG16 architecture and CNN algorithm, were selected among the several deep learning algorithms in the experimental work. The selection process seeks to identify the algorithm that minimizes loss while producing the best accuracy. The study technique's main objective is to use deep learning to identify and classify different bird species. The study makes use of the CNN algorithm with skip connection and convolutional neural network architecture models, such as VGG16. It is possible to find traits that are helpful for correctly recognizing various bird species through this model.

By keeping an eye on each type of bird, the development of a system for classifying birds can help officials monitor the birds in a particular area.

1.3. Research Contribution

This section encompasses the contributions of the present research article.

This paper provides an overview of recent developments in the field of machine learning and deep learning techniques for bird identification and prediction. The research completed between 2018 and 2023 is included in the study, providing a comprehensive understanding of the state-of-the-art techniques and approaches used in this field.

The literature has explored multiple datasets and algorithms associated with the detection of bird species.

The study technique's main goal is to identify and categorize bird species employing Deep Learning. The study uses convolutional neural network architecture models, such as VGG16. The architectural layer of these models allows the identification of helpful properties for correctly recognizing bird species. The importance of machine learning in tackling difficult challenges in bird species is shown by the study's focus on the application of Deep Learning and these sophisticated architecture models. With the use of potent deep learning algorithms, the research methodology offers a potential strategy for detecting and classifying bird species from photos. This method could greatly contribute to the creation of effective and durable disease management plans for the agriculture sector.

2. Literature Review

While numerous work has been accomplished on the identification of diseases from image datasets using Deep Learning and Convolutional Neural Network based algorithms, Limited effort has been dedicated to identifying bird species from image datasets of birds. Literature review examines the methods that are currently in use for classifying images using transfer learning techniques.

In this [1] the classification of bird species was done by using the Convolutional Neural Network(CNN).This research [2] presented a deep learning technique to more accurately identify many different bird species from their calls. The suggested approach combined coordinated attention with long short-term memory. Xeno-Canto provided almost 70,000 bird-call audio clips, spanning 264 different bird species. According to an evaluation experiment, the proposed network's mean average precision was 77.43%. The main objective [3] is to develop and evaluate a sophisticated framework for carrying out the identification of bird species by utilizing deep learning convolutional neural networks (DCNNs) to analyze audio spectrogram input. This research [4] main objective is to present an overview of the Life CLEF 2022 evaluation, with a particular emphasis on machine learning-based methods for predicting species distribution and identification. It seeks to advance the field of biodiversity research and educate participants, practitioners, and experts on the state of the art and new developments in this field of study. Birds species classification [5] was done by machine learning algorithms, In the test data set, an automated model based on deep neural networks is presented in this work [6]that can identify the species of bird automatically. When tested with the test datasets, the model had a promising accuracy of 98%. The model was trained and tested for 253 species of birds, with a total of 7637 and 1853 photos for the train and test, correspondingly. The main objective of this [7] probably will be to show how well spectrograms and an MLP classifier work sound together for automated bird species identification. This research [8] presents a deep learning network that can recognize individual birds from a given input image. Preferring to use pre-trained CNN networks with base model and pre-trained ResNet model in addition to encode images. A classification accuracy of 97.98% was achieved. The single-lens reflection camera with telephoto lens [9], a motorized video head, and a radar constitute the recommended system for automatic bird identification. For image categorization, a convolutional neural network that has been trained using a deep learning algorithm is used. Additionally propose a technique for data augmentation that involves rotating and converting photos to match the appropriate color temperatures. Several deep learning oriented models, including SSD, YOLOv4, and YOLOv5, are evaluated in this study [10] for the identification and classification of bird species. All models are tested using the CUB-200-2011 dataset, which is accessible to the public. With a 96.99% map score, 94.27% F-1 score for 20 classes, 93.94% precision, 94.34% recall, and 95.43% accuracy, the YOLOv4 model performs better than the most contemporary cutting-edge methods. With the help of convolutional neural networks [11]to extract information from images, this study attempts to investigate the application of deep learning for bird recognition. The database used for the analysis included 4340 pictures that the paper's author had gathered from Jordan. Artificial neural networks (ANN) outperformed other classifiers in terms of classification accuracy (70.9), precision (0.71), recall (0.71), and the F-measure (0.70), according to the classifier findings. A deep learning neural network method for species identification of birds is presented in this piece of work [12]. The implementation makes use of the Tensor Flow Framework. Birds are amazing creatures that keep an eye on the planet's resources for preservation. They are directly connected to the atmosphere. This study [13] predicts bird species using characteristics found in the song spectrum. Machine learning algorithm used .This work [14] aims to identify different Bangladeshi native bird species using imagery data. To complete this study, the Mobile Net and Inception-v3 models have been primarily used for image categorization. The Mobile Net algorithm with transfer learning performs better than the other models and achieves a test accuracy of 91.00%. Testing the ability of cutting-edge deep learning architectures to identify birds in webcam-captured images was the main goal of this work.[15] For this investigation, 10592 images in total were gathered. This study[16] identifies images of birds using a deep convolutional neural network The author employed a model based on the ResNet152 method, which had a validation rate of 95.52% and an AlexNet test accuracy of 89.48%, which was the lowest. It has been demonstrated that classifying bird images using a deep convolutional neural network is effective and beneficial. This study [19] shows, with remarkable attention to detail and a strong commitment to bird preservation, the challenges faced by birds and the habitats in which they reside. Using a combination of statistical analysis and first-hand observations, the author sheds light on the alarming trend of declining bird populations and highlights the urgent need for action. The result is an insightful and thought-provoking piece that will open readers' eyes to new perspectives when it comes to planet's feathery companions. The VGG 16 network was utilized in this study [22] to extract bird traits. The dataset of Bangladeshi bird species was used by the author. Although the author employed a variety of categorization techniques, including random forests and K-nearest neighbors (KNN), the support vector machine (SVM) yielded the highest accuracy of 89%. A paper that makes use of the Internet of Birds mobile app and a deep learning platform to recognize photographs of different bird species [23]. Convolutional neural networks (CNNs) were employed by the author to identify various aspects in photos. By using the skip connection method, feature extraction is improved. After that, a probability distribution of the bird features is obtained using the Soft Max function. Convolutional neural networks (CNNs) had an accuracy of 93.98%, while support vector machines (SVMs) achieved 89.00% accuracy. The maximum accuracy of the suggested model convolutional neural network (CNN) with skip connection is less than 99.00% for both accuracies. According to this study [24], changes in the ecosystem are caused by a decline in the number of bird species.

For more than 48 years, authors examined the avifauna of North America. It is discovered that there is a 29% decline in the avian population from 1970. For biodiversity to survive in the future, this population decline must be addressed[26]. The average, standard deviation, and asymmetry of the blue, red, and green (also known as RGB planes are among the nine color based measures that can be detected in bird images. The SVM technique was used for classification and extraction of features. The multiple category objects in a picture were predicted to be located using a quick recognition model called SDD as well. The SVM classifiers were trained using the method known as stochastic gradient descent (SGD) method.

3. Gap Analysis

Some work had already been done on the bird's species prediction. In Gap analysis, finding the gap studying previous research is shown in a tabular format. This research work is different from others. Here, a tabular description of the findings in relation to earlier studies is provided. Table 1 presents a comprehensive overview of the key features incorporated into the 'birds species prediction and recognition ''.These features have been thoughtfully designed to enhance user experience and functionality. The proposed table provides a concise summary of the application's capabilities, including bird prediction and recognition through computer vision. Each feature in Table 1 is described briefly, highlighting its significance within the application's ecosystem. Refer to this table to gain insights into the diverse functionalities offered by bird species prediction and recognition. Table 2 lists the top 14 research papers that have been read and examined to obtain information about bird species prediction and recognition. Table 3 serves as a comprehensive mapping that correlates the sources referenced in the Source Table 2 with the specific features incorporated into the bird's species prediction and recognition. In these tables, each feature is listed alongside the relevant sources that influenced its inclusion in this research. This mapping provides valuable insights into the research papers that directly inform the development of individual features within the application.

Table 1. Feature Table

F#	Name	Description
FT1	Machine Learning	The paper employs the concept of machine learning in its research methodology.
FT2	Deep Learning	The research methodology in the paper incorporates the use of Deep Learning.
FT3	Dataset images	Whether the application is using Dataset for training.
FT4	video	Detecting birds species through video
FT5	Sounds	Whether Sounds Dataset is used to train models for identification.
FT6	Google Map API	For location feature whether Application is using Google Map API.
FT7	Desktop / Web App	Whether the project is Desktop/Web Application based.
FT8	Mobile Application	Whether the project is based on Mobile Application.
FT9	Camera	For input Whether the Application is using camera
FT10	Microphone	For taking input whether Application is using a Microphone.

FT11	Augmentation	Whether the research methodology is using Augmentation to enrich datasets
FT12	Color segmentation	Whether the research methodology is used for categorizing image regions.
FT13	CNN Algorithm	Paper approaches CNN algorithm for identifying bird species.

Table 2. Source Table

S#	Source Name
S1	"Birds Species identification using Convolution neural network"
S2	"An Efficient Model for a Vast Number of Bird Species Identification Based on Acoustic Features"
S3	"Bird Species Identification Using Spectrogram Based on Multi-Channel Fusion of DCNNs"
S4	"Overview of LifeCLEF 2022: An Evaluation of Machine-Learning Based Species Identification and Species Distribution Prediction"
S5	"Machine learning for image based species identification"
S6	"Automated Bird Species Identification Using Neural Networks"
S7	"Sound-spectrogram based automatic bird species recognition using MLP classifier"
S8	"PakhiChini: Automatic Bird Species Identification Using Deep Learning"
S9	"Deep Learning Case Study for Automatic Bird Identification"
S10	"Bird Species Classification from Images Using Deep Learning"
S11	"Birds Identification System using Deep Learning "
S12	"Deep Learning Neural Network for Identification of Bird Species"
S13	"Component Species Prediction of Birds with Song Spectrum Features Using Machine Learning"
S14	"Recognition of local birds of Bangladesh using MobileNet and Inception-v3"

Table 3. Sources and Features

	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12	S13	S14	Proposed work
FT1	×	✓	×	✓	✓	✓	×	✓	✓	×	✓	×	×	✓	✓
FT2	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	×	×	✓	✓
FT3	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	×	✓	✓	✓
FT4	×	×	×	×	×	×	×	×	×	×	×	×	×	×	×
FT5	×	×	×	×	×	✓	✓	×	×	✓	×	×	×	✓	×
FT6	×	×	×	×	×	×	✓	×	×	×	✓	×	×	×	✓
FT7	×	✓	✓	✓	×	×	×	✓	✓	×	✓	×	×	×	×
FT8	×	×	×	×	×	✓	✓	×	×	✓	×	×	×	✓	✓
FT9	×	×	×	×	×	✓	✓	×	×	✓	×	×	×	✓	✓
FT10	×	×	×	×	×	✓	✓	×	×	✓	×	×	×	×	×
FT11	×	×	×	×	×	×	✓	✓	×	✓	✓	×	×	✓	✓
FT12	×	✓	×	✓	✓	×	✓	✓	×	×	×	×	×	×	×
FT13	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

3.1. A comparison of literature on Birds prediction using Deep Learning

Recent years have seen major advancements in the field of bird species detection due to the integration of both ML (machine learning) and DL(Deep learning) techniques. The capacity to accurately and efficiently identify and categorize bird species has been transformed by these cutting-edge technology. Features that are manually engineered have been used for feature extraction and classification, and machine learning techniques like Random Forests and support vector machine learning have been instrumental in this process. On the other hand, a subset of Deep Learning algorithms known as Convolutional Neural Networks (also referred to as CNNs have demonstrated remarkable capacity for autonomously acquiring hierarchical representations from raw data, such as images or audio files of birds. Considering these algorithms in table 4. The comparison in Table 4 is based on earlier research, and as things develop, there is a lot of potential for ecological monitoring, conservation initiatives, and scientific research when using cutting-edge technologies for bird species detection

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Table 4. Comparison with state of art work

Ref	Year	Algorithm	Accuracy
[1]	2022	CNNs, or convolutional neural networks	94%
[2]	2020	CNNs, or convolutional neural networks	90%
[3]	2021	CNNs, or convolutional neural networks	93%
[4]	2020	CNNs, or convolutional neural networks	85%
[5]	2019	CNNs, or convolutional neural networks	92%
[6]	2020	CNNs, or convolutional neural networks	93%
[7]	2021	Artificial Neural Network (ANN),	87%
[8]	2022	CNNs, or convolutional neural networks	95%
[9]	2019	CNNs, or convolutional neural networks	80%
[10]	2019	CNN, Yolo v5	93%
[11]	2022	CNNs, or convolutional neural networks	85%-90%
[13]	2023	CNNs, or convolutional neural networks	91%
[14]	2021	CNNs, or convolutional neural networks	85%
[16]	2021	ResNet152 , Alex Net	95.52%, 89.48
[27]	2017	Support Vector Machine	98.33%

4. Methodology

4.1. Dataset

The dataset has been carefully selected to include a broad variety of bird species from various families, genera, and orders, which accurately reflects the whole range of bird biodiversity. There are a good number of wonderful images of every species, capturing different viewpoints, positions, and settings. It is ensured that the model learns to distinguish between commonly encountered birds and those that are less common but equally important for biodiversity evaluations by including both common and rare species. Additionally, the collection purposefully includes a wide range of ecosystems. Birds live in a variety of habitats, including metropolitan areas, coastal regions, and dry deserts and rainforests. The system learns to recognize species in various biological habitats by including images from these unique locations. This approach improves the accuracy of the model while also promoting a better comprehension of how these species interact and adapt to their environments.

The dataset comprises 28,927 training pictures (about 55 pictures each species) and 2,625 evaluation images (five images each species), for a total of 525 bird species. This is an interesting superior in quality dataset where each image has a single bird that typically occupies at least half of the pixel count. Due to these attributes, the training and testing accuracy of a very complex model has reached 90%. Every image is real and hasn't been manipulated in any way. Every image is in JPG format, measuring 224 x 224 pixels and having a color depth of three channels (RGB). The dataset is divided into three sets: training, test, and validation. Each set has 525 sub-indices that represent different bird species. When creating training, testing, and validation data with Keras Image Data Generator.flow_from_directory, the data structure comes in convenient. Consequently, utilizing these datasets is likely to result in the highest accuracy for your model. All images identified as duplicates or near-duplicates were removed to avoid sharing them between training, testing, and validation sets. The cropping image of the dataset is adjusted to ensure that the bird occupies a minimum of 50% of the image's pixels. Subsequently, the image is resized to the dimensions of 224 x 224 x 3 in JPG format as shown in Table 5. By cropping and shrinking the image, making sure that CNN processes it with enough information to produce a very accurate categorization. Furthermore, each file has a sequential number, with one file for each species. The test pictures are thus named 1.image through 5.image. For confirmation photos, the same sequential numbering with zero padding is used. 001.image, 002.image,... 010.image, 011.image,... 099.image, 100.image, 102.image, and so on are some examples. When utilizing Python file functions and Keras streams, it is ensured that file order is maintained by using zero padding. The ratio of male species and female species is the major gap in the literature. Approximately 80% of the images feature men, while the remaining 20% depict women. Males exhibit a greater variety in coloration, whereas the females of the species are generally solid. As a result, the representations of men and women can be very different. Almost all photographs used for testing and validation were taken with males of this species. As such, the classifier might not work as well on images of female specimens.

Figure 3. Dataset (525 classes)

With a strong emphasis on biodiversity, the dataset for the 525 bird species classification model includes a wide range of species, habitats, and sizes.

Table 5. Dataset Description

Dataset break	Detail of Dataset
Train	28927
Test	2625
Valid	2625
Size	224 x 224 x 3
Type	Jpg
Pixel	50%
Classes	525

4.2. Bird Species Identification Deep Learning Framework

The development of a Deep Learning Model that can help in identifying kinds of birds with accuracy is the goal of this research. For this, well-known convolutional neural network (CNN) architectures like VGG16 and Inception were used. For the identification system to be trained and tested for bird picture recognition, a reliable dataset is essential. Therefore, Kaggle have been employed, which has a large number of photos of birds in both front and back. To guarantee that the training data had enough variety, the dataset underwent preprocessing and augmentation. Test, training, and validation sets were then created from the preprocessed dataset.

Deep learning models are now the most widely used approach for artificial intelligence and big data research. The advent of deep learning [24] techniques has led to an increase in the complexity of computer vision and picture identification challenges. The deep learning (DL) based model that this study suggests has a great deal of promise to help with bird species identification. The suggested deep learning model that was created using the CNN architecture to produce this technique for classifying bird images is described below. The test set was used to evaluate the performance of the top-performing model, which was identified based on the accuracy of the validation set. The evaluation parameters included F1 score, recall, accuracy, and precision.

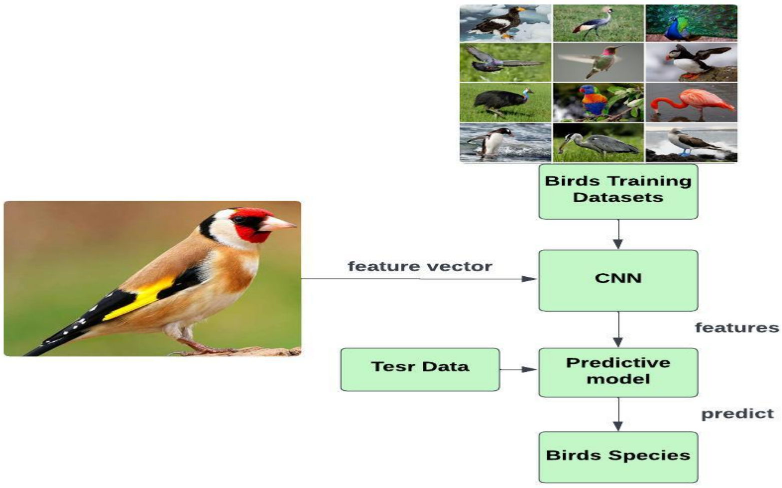


Figure 4. The idea of the extraction of features

4.2.1. CNN, or Convolutional Neural Network

Convolutional Neural Networks (CNNs) are a unique type of artificial neural network designed to analyses grid-like data efficiently. They are especially well-suited for tasks that involve images and motion pictures or videos. CNNs excel at tasks related to pattern recognition and image analysis. convolutional layers serve as the fundamental building blocks of CNNs. They consist of filters or kernels that slide across the input data (e.g., an image) to perform a mathematical operation called convolution. Features in the input data such as edges, corners, and textures can be identified with the use of convolution. A convolutional layer receives an image as input and outputs a number of feature maps. The input image may have many channels, such as RGB, meaning that the convolutional layer needs to learn how to translate one 3D volume into another 3D volume. The layer is made up of several convolution kernels with movable weights. Stochastic gradient descent is used to update these weights during the optimizing phase. One feature map is produced for each kernel in the convolutional layer as a result of the discrete convolution between each kernel and the input volume. The suggested neural network is a deep learning system that can automatically distinguish between distinct photos by taking in input images, assigning weight to different parts of the images, and doing so as shown in Figure 5. The computer's pixel values are all that makeup the input image.

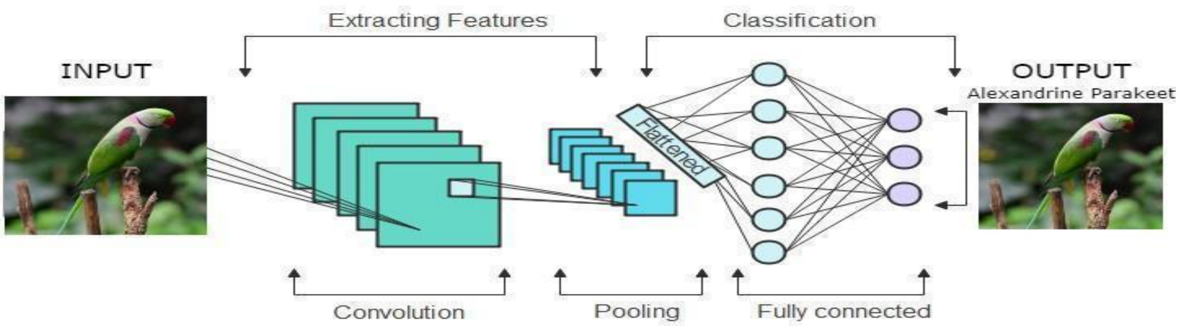


Figure 5. CNN model architecture

Fewer variables reduce the amount of data required to train the model, which expedites the learning process. This is one of the practical advantages. A convolutional layer stack comprising an input layer, two Fully Connected (FC) layers, and a final output the softmax layer was employed in the CNN model-building process to identify different species of birds. Convolutional layers process the input using a convolution operation, passing the resultant data to the subsequent layer as shown in Figure 5. Each convolutional layer was made up of two components: batch normalization (BN) and 5*5 convolution. It is a method for standardizing the inputs to a layer for every mini-batch in order to train incredibly deep neural networks. As a result, the learning process becomes more stable and the quantity of training epochs needed to train deep networks is greatly decreased. (c) Activation of the rectified linear unit (the ReLU): The operation is individually linear. It will output 0 if it is negative; otherwise, it will generate the input immediately. and (d) layers for pooling: By combining the outputs of neuron clusters in one layer into a single neuron in the layer below, the pooling layers reduce the complexity of the data being collected.

4.2.2. VGG16 ((Visual Geometry Group 16)

A particular Convolutional Neural Network, architecture is called VGG16. This model is famous for its simplicity of design and also effectiveness in tasks related to image classification. The VGG16 is part of the VGG family of models, which includes variants with different numbers of layers (such as the VGG19).

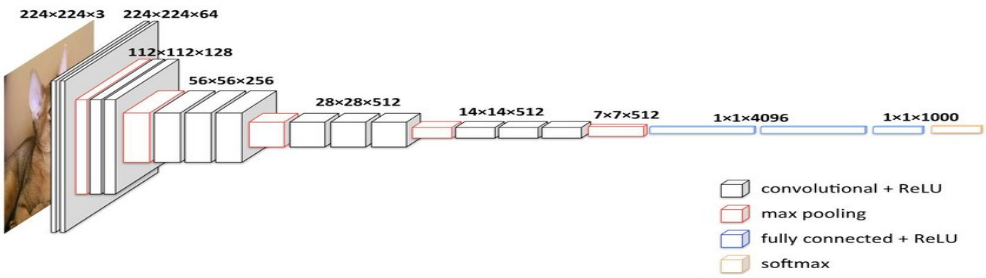


Figure 6. VGG16 model architecture

4.2.3 Skip Connection

A notion developed in deep neural networks, specifically in the context of convolutional neural networks (CNN algorithms.), is a skip connection, also referred to as a residual link. With skip connections, the vanishing gradient issue is lessened and data may move between layers more efficiently, making it easier to train very deep networks. In a typical neural network section, the result of one layer becomes the input for the layer that follows. The idea of skip connections is to add a shortcut or direct link that bypasses one or more layers. Data can go directly from the input to the output by utilizing this shortcut, creating a "skip" else "residual" connection.

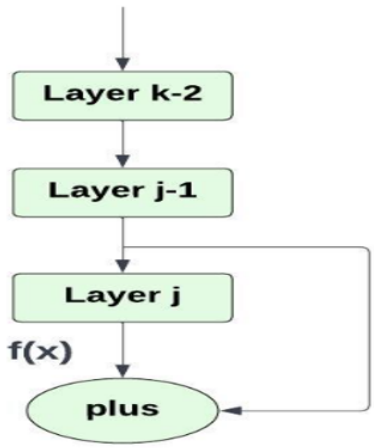


Figure 7. Framework of Skip-Connection

As seen in Figure 7, skip connections is suggested [27] between similar convolutional layers to address and quantify the extent to which a given layer is generic or specialized. Equation (i) suggests that the skip layer connections ought to improve the extraction of features by using a weighted summing of the associated layers.

$$m(x) = (1 - alpha)\ f(x) + alpha(x) \quad (1)$$

where x is the input to a specific layer, m(x) is a linear combination of f(x) and x, f(x) is a function of input x, and α(alpha) is a weight in the unit interval [0,1].The result from the layer before it contributes less to overall performance than the layers before it if the amount of weight α is greater than 0.5. Moreover, the output from the layer before it contributes more to the total performance if the weight α is less than 0.5. By using the skip link feature utility, stabilize training, and converge is provided.

4.2.4. Feature Extraction

The feature extraction procedure for identifying bird species from bird photos is explained in this subsection. The process of feature extraction entails taking significant representations and patterns out of the images. The feature vectors that were taken out of the raw data (an image of a bird) during the feature extraction process are sent to the CNN, which has been trained using the training dataset. The predictive model receives the extracted features and uses them to compare them with the test data. Next, the algorithm predicts the species of that specific bird in the image. Taking important representations and patterns out of the images is the process of feature extraction. Figure 4 depicts this feature extraction paradigm. ReLU was used to compute the features.

4.2.5. Platform Utilized

The platform that was used in the article has a 6 GB Intel Core i5 CPU running at 2.50GHz and a 64-bit operating system. Google Colab is use to run the source code. The Collaboratory, sometimes known as "Colab," is an innovation of Google Research. Every one may write and execute any Python code online with Colab. It is very beneficial for data analysis, teaching, and machine learning. Colab is a shared Notebook Jupyter solution that doesn't require installation and provides public access to hardware, including GPUs [25]. The Matplotlib data visualization software is used to plot model performance graphs.

4.2.6. System Implementation Workflow

This subsection describes how the suggested deep learning platform will be used to identify the different bird species. The bird's image is supplied to the system as input.

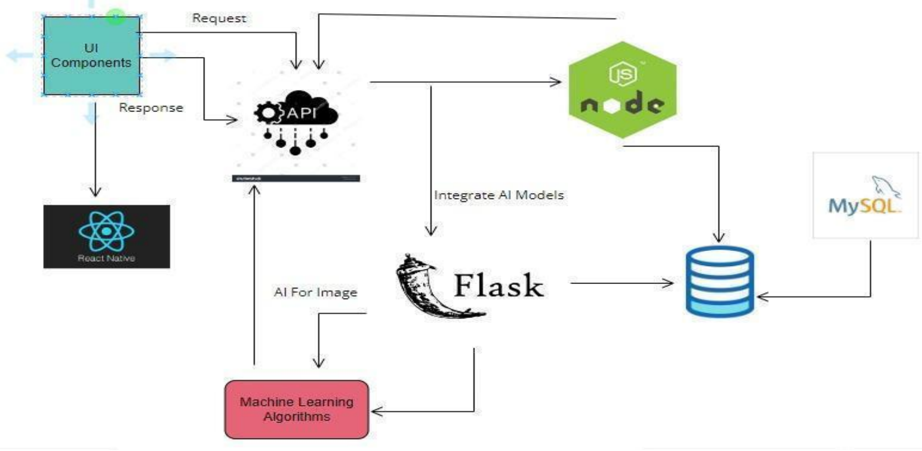


Figure 8. System Architecture

To conclude this species identification operation, a client-server architecture is set up. Client computers provide an interface via which a computer user can ask the server for services and see the results that the server provides. Figure 6 depicts the client-server architecture, shows that the application is made by using react native. The end-user device sends prediction requests for bird photos to the server. The system notifies the user of an error if the image is not one of a bird. If the image is of a bird, the system should process it using the suggested deep learning model. Front end displays all the screens of applications for example home, feedback, and sign up etc. on react native framework. The backend is on the node js. The model is trained on python by using different algorithms of deep learning and then the model is integrated with react native application through flask API and MySQL is use for the database.

5. Result

The specifics of the system's experimental findings for identifying bird species are explained in this section. This suggested deep learning system can be used to distinguish and forecast between photos of birds and non-birds. When non-bird images are uploaded to the identification system, the bird species identification system produces an error warning instructing the user to contribute only images that feature a bird. Table 6A represents the result on 20 species the good accuracy on CNN with skip connection was achieved. Using the test image datasets, the built-in model was successfully tested, and as table 6A illustrates, the model's overall accuracy was found to be 92%.

Table 6a. Results using CNN and VG16

Test on Dataset	Algorithm	Accuracy
20 Species	CNN with skip connections	0.92
20 Species	VGG16	0.895
525 Species	VGG16	0.60

5.1. Confusion Matrix

For the confusion matrix, 5 classes are considered from the dataset. Then 20 images are taken from the view of these five classes. Then these 20 images were tested one by one from the trained Model.

Table 6b. Confusion matrix of specific birds test

Birds name	American avocet	American bittern	American coot	American goldfinch	American kestrel
American avocet	19	0	0	0	0
American bittern	0	19	0	0	0
American coot	0	0	18	0	0
American goldfinch	1	0	0	13	0
American kestrel	1	0	0	0	14

AMERICAN AVOCET	AMERICAN BITTERN	Americane Coot	Americane Goldfinch	Americane kestrel
correct	correct	correct	correct	correct
correct	correct	correct	correct	correct
correct	correct	(Wrong) ALBATROSS	correct	correct
correct	correct	correct	(Wrong) AFRICAN FIREFINCH	(Wrong) AMERICAN AVOCET
correct	correct	correct	(Wrong) ABBOTTS BABBLER	correct
correct	correct	correct	correct	correct
correct	correct	correct	correct	correct
correct	(Wrong)ABBOTTS BABBLER	correct	(Wrong) ALBERTS TOWHEE	(Wrong) ALBERTS TOWHEE
Wrong(Albatross)	correct	correct	(Wrong) ALTAMIRA YELLOWTHROAT	correct
correct	correct	correct	correct	correct
correct	correct	(Wrong) AFRICAN OYSTER CATCHER	correct	correct
correct	correct	correct	(Wrong) AMERICAN AVOCET	(Wrong) ALBATROSS
correct	correct	correct	correct	correct
correct	correct	correct	correct	(Wrong) ABBOTTS BABBLER
correct	correct	correct	correct	(Wrong) ALBERTS TOWHEE
correct	correct	correct	(Wrong) AMERICAN FLAMINGO	(Wrong) AFRICAN EMERALD CUCKOO
correct	correct	correct	(Wrong) ABBOTTS BABBLER	correct
correct	correct	correct	correct	correct
correct	correct	correct	correct	correct

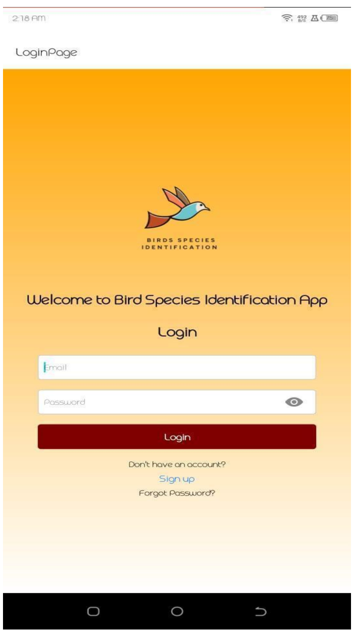
Figure 9. Testing bird species

Here is the table of tested results. Some predictions are not from these classes which are taken for test but it is from the remaining dataset so it didn't mentioned in the confusion matrix table. The calculation performed is in Table 7. the higher the F1 score and the recall.

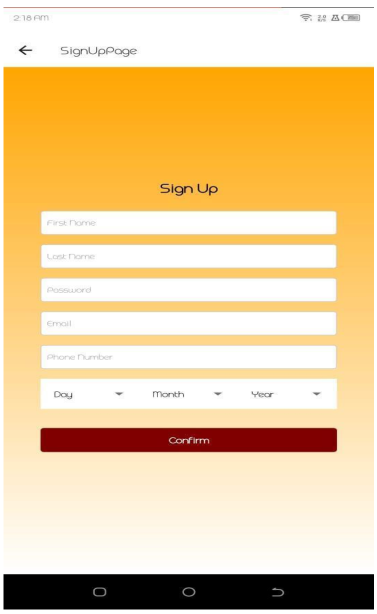
Table 7. Performance metric for different bird species

For class a (American Avocet)	For class b (American Bittern)	For class c (American Coot)	For class D (American Goldfinch)	For class E (American Kestrel)

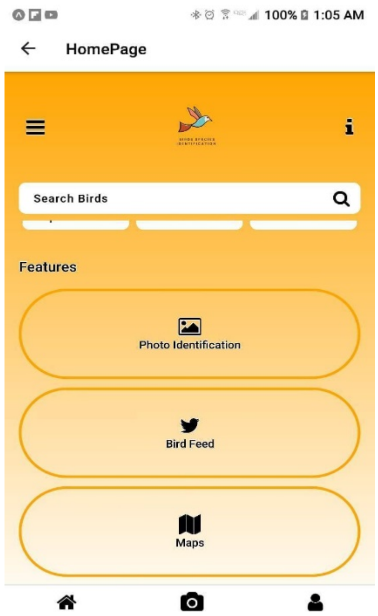
Precision (class a) = TP/TP+FP Precision (class a) = 19/19+0 Precision (class a) = 1	Precision (class b) = TP/TP+FP Precision (class b) = 19/19+0 Precision (class b) = 1	Precision (class c) = TP/TP+FP Precision (class c) = 18/18+0 Precision (class c) = 1	Precision (class c) = TP/TP+FP Precision (class c) = 13/13+0 Precision (class c) = 1	Precision (class E) = TP/TP+FP Precision (class E) = 14/14+1 Precision (class E) = 0.93
Recall (class a) = TP/TP+FN Recall (class a) = 19/19+2 Recall (class a) = 0.90	Recall (class b) = TP/TP+FN Recall (class b) = 19/19+0 Recall (class b) = 1	Recall (class c) = TP/TP+FN Recall (class c) = 18/18+0 Recall (class c) = 1	Recall (class D) = TP/TP+FN Recall (class D) = 13/13+0 Recall (class D) = 1	Recall (class E) = TP/TP+FN Recall (class E) = 14/14+0 Recall (class E) = 1
F-1 Score (class a) = 2 * Precision*Recall / Precision + Recall F-1 Score (class a) = 2 * 1*0.90 / 1+0.90 F-1 Score (class a) = 0.94	F-1 Score (class b) = 2 * Precision*Recall / Precision + Recall F-1 Score (class b) = 2 * 1*1 / 1+1 F-1 Score (class b) = 1	F-1 Score (class c) = 2 * Precision*Recall / Precision + Recall F-1 Score (class c) = 2 * 1*1 / 1+1 F-1 Score (class c) = 1	F-1 Score (class D) = 2 * Precision*Recall / Precision + Recall F-1 Score (class D) = 2 * 0.92*1 / 0.92+1 F-1 Score (class D) = 0.94	F-1 Score (class E) = 2 * Precision*Recall / Precision + Recall F-1 Score (class E) = 2 * 0.93*1 / 0.93+1 F-1 Score (class E) = 0.96



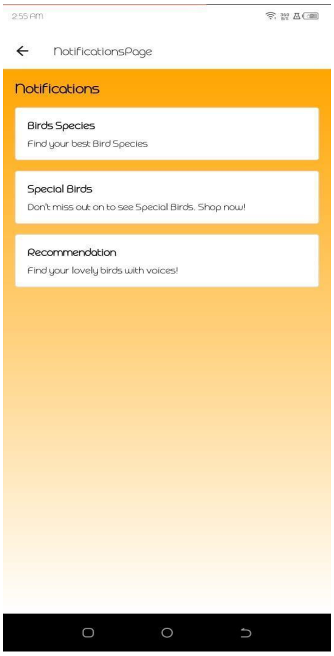
10a. Login Page

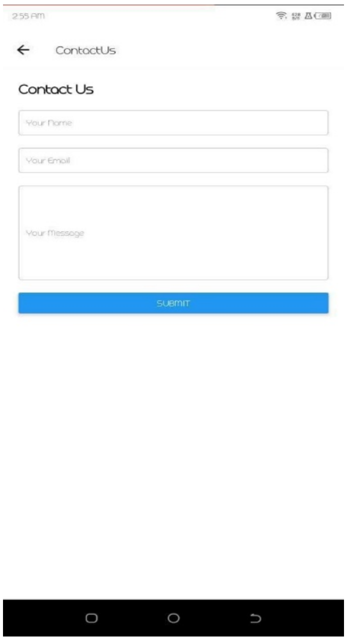


10b. Signup Page



10c. Homepage





10d. Notifications	10e. Contact Us	10f. feedback screen

Figure 10. Bird species prediction application Screens

This specific area or screen figure 10a to 10f in the mobile application the Bird Info Screen offers comprehensive details about various bird species identification. This application is knowledgeable for Bird watchers.

The major goal of making this screen was to instruct people on how to quickly recognize different bird species. Comprehensive details about the many bird species are shown in the screen's main section. Table 7 displays the prediction results for photographs uploaded via an end-user device.

In this model, 20 epochs run for better accuracy. To train machine learning models, particular datasets are sent through the algorithm. The number of times an algorithm runs through a dataset is called an epoch. In the context of machine learning, epoch denotes the entirety of the algorithm's processing of the training data. The accompanying Figure 9 graph shows the accuracy of the model. It was plotted using epochs on the x-axis and accuracy rate on the y-axis.

Table 8. Prediction Outcomes for Pictures Sent from An End User Gadget.

Test ID	Input	Actual Output	Expected Output	Status
01	 **Figure 10a.** Identified Bird Species Name.	American Kestrel	American Coot	FAIL

02		American Avocet	American Avocet	PASS

Figure 10b. Identified Bird Species Name.

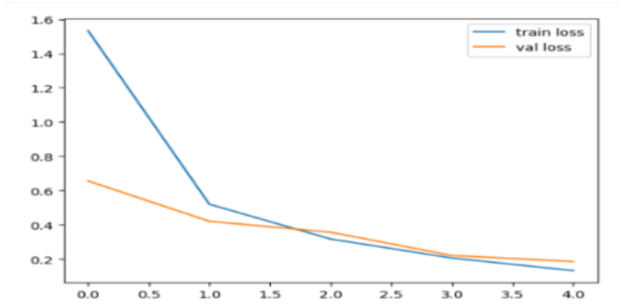
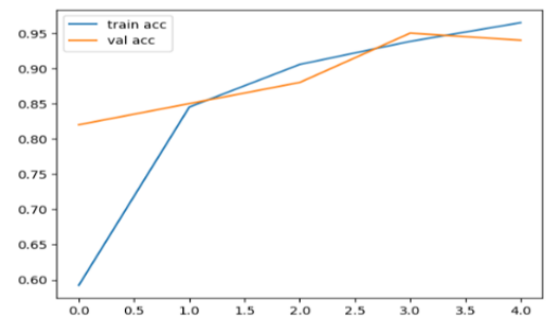
a: Training loss C	b: Training Accuracy
	

Figure 11. Model results

6. Conclusion

In contemporary times, the scarcity of bird species and the difficulty in identifying them visually pose challenges. To address this, a multi-scale Convolutional Neural Network, combined with data augmentation techniques, will be utilized. The literature review extensively explores diverse techniques for bird identification, elucidating the limitations of existing systems. To overcome these drawbacks, a proposed method aims to elevate accuracy levels to a range of 85-95%. The research work is to set out to improve the classification accuracy of the bird species many bird species are endangered or on the verge of extinction, and people are unaware of the existence of these rare species. As a result, applications developed using this model will be useful in identifying endangered species and in raising public awareness of the need for all species to survive in harmony with nature. The proposed framework suggests that Deep Convolutional neural networks CNN with skip connection is the most effective method for classifying and analyzing visual data. Through an analysis of the data set, the researchers discovered that certain bird species are more difficult to classify than others and that there is a noticeable disparity in the relative number of training samples for each species of bird. This appears to cause favoritism or overprediction from the model of the species of bird with the most recordings. The research found through an analysis of the data set used that the relative number of training samples for each bird species is quite uneven, which seems to lead to a favoritism, or over-prediction, from the model of bird species with the most recordings, and that some bird species are harder to classify than others. The 92% accuracy in identifying bird species is a major step forward for ecological research and conservation. The practical ramifications include enhanced biodiversity studies, better ecological monitoring, more successful conservation tactics, and greater participation from citizen scientists. This development is a great help to communities, researchers, and conservationists who are trying to preserve and comprehend the complex dynamics of bird life.

7. Future work

Monitoring emerging technology and trends in bird watching will guide future updates and enhancements of the Bird identification application. The forthcoming modifications to the mobile application include the incorporation of a sound identification module. A dataset of sound sets will be the focus of future efforts. The Bird identification application will integrate this sound dataset during the model training phase. The dataset expansion is planned to refine the Bird identification application, utilizing substantial datasets for more precise and accurate results.

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