AUTOMATED AVIAN IDENTIFICATION: A DEEP LEARNING FRAMEWORK FOR ENHANCED BIRD SPECIES CLASSIFICATION THROUGH VISUAL AND ACOUSTIC ANALYSIS

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ABSTRACT

For the labor-intensive and time-consuming task of identifying and classifying bird species, ornithologists and ecologists frequently rely on manual observation. Subjectivity in visual recognition and a narrow coverage in auditory data collecting are two drawbacks of conventional methods like field guides and acoustic monitoring. Furthermore, non-experts may find manual techniques difficult, and they might not offer current information on bird populations and the ecological relationships among them. We present a cutting-edge deep learning method that uses neural networks' ability to automatically recognize and categorize different bird species based on auditory and visual inputs in order to get around these limitations. Conventional bird identification uses field guides, which have limitations based on the user's skill level and might result in incorrect classifications because of seasonal variations in bird plumage. There are disadvantages to acoustic monitoring devices as well, such as the need for professional interpretation and the loss of visual clues. The accuracy and efficiency of bird population monitoring is limited by these labor-intensive and sometimes incomplete procedures. As a result, the identification and categorization of bird species require a more reliable and automated method. Convolutional Neural Networks (CNNs) are used in our suggested Deep Learning-based Approach for Bird Species Identification and Classification to analyze both visual and audio data. Large, annotated datasets of bird photos and audio recordings will be used by the system to train a deep learning model that will be able to accurately identify and categorize different bird species. In addition to identifying species, the model will take into account a number of other variables, including seasonal changes in feather color and bird sounds. Furthermore, our technology will enable real-time monitoring using field-deployable hardware and mobile applications, giving immediate insights on bird populations and their activities. Our suggested solution would greatly improve the efficiency and accuracy of bird species identification and categorization by automating the procedure and utilizing deep learning. This will aid in the study of avian habitats and aid conservation efforts.

1. INTRODUCTION

1.1 Overview

Bird classification serves as a fundamental tool in understanding the diversity and evolutionary relationships among avian species. By categorizing birds into different groups based on shared characteristics such as morphology, behavior, and genetic makeup, scientists can gain insights into their evolutionary history, ecological roles, and conservation needs. Classification helps organize the vast array of bird species into manageable groups, allowing researchers to study them more effectively. Moreover, it facilitates communication and collaboration among scientists, enabling them to exchange information about bird species across different regions and disciplines.

Furthermore, bird classification is crucial for conservation efforts aimed at protecting threatened and endangered species. By identifying species that are at risk of extinction and understanding their relationships to other species, conservationists can develop targeted strategies to conserve habitats, mitigate threats, and implement management plans. Classification also provides a framework for monitoring changes in bird populations over time, assessing the impacts of environmental disturbances, and identifying priority areas for conservation action.

In addition to its scientific and conservation implications, bird classification also holds cultural and educational significance. It allows bird enthusiasts, birdwatchers, and citizen scientists to better understand the birds they encounter in their natural habitats. By learning about the characteristics and relationships of different bird species, individuals can develop a deeper appreciation for biodiversity and the importance of preserving natural ecosystems. Overall, bird classification serves as a cornerstone of ornithology, contributing to our knowledge of birds and informing efforts to conserve them for future generations.

1.2 History

Deep learning has emerged as a powerful tool for bird species classification in recent years, but its integration with enhanced camera features is a relatively new area with exciting developments. Here's a glimpse into the history of this project:

Early Efforts (2010s)

Traditional methods: Bird species identification relied heavily on hand-crafted features like color histograms and texture analysis. These methods achieved moderate accuracy but lacked the flexibility and scalability of deep learning.

First deep learning approaches: Convolutional Neural Networks (CNNs) started showing promise in image recognition, including bird classification. However, datasets were limited, and models were computationally expensive.

Advancements (2015-2020)

Large datasets: Initiatives like eBird and the Macaulay Library amassed vast image collections, enabling training of deeper and more accurate models.

Transfer learning: Pre-trained models like ResNet and VGG, trained on massive image datasets like ImageNet, were adapted for bird classification, significantly boosting accuracy.

Exploration of enhanced features: Initial studies investigated the use of depth information from LiDAR for 3D bird shape analysis and thermal imaging for nocturnal species detection.

Recent Developments (2020-present)

Focus on efficiency and real-time applications: Lightweight models like EfficientNet and MobileNet are being explored for mobile devices and field applications.

Integration of diverse features: Research is actively exploring the combination of RGB, depth, thermal, and hyperspectral data for more robust and comprehensive classification.

Explainable AI: Techniques are being developed to understand the model's decision-making process, crucial for interpreting results and building trust.

1.3 Problem Statement

Accuracy limitations: Existing deep learning models for bird species classification, although powerful, still struggle with achieving perfect accuracy, especially for challenging cases like similar-looking species, poor image quality, or complex backgrounds.

Limited data: Training deep learning models often requires vast amounts of labelled data, which can be scarce for certain bird species or specific geographic regions.

Standard RGB limitations: Standard RGB cameras capture only visible light, potentially missing crucial information for differentiating species based on subtle plumage differences or nocturnal activity.

This project aims to address these limitations by:

Developing a deep learning model that achieves high accuracy in bird species classification, surpassing the performance of existing models.

Leveraging enhanced camera features beyond standard RGB images, such as depth, thermal, or hyperspectral data, to capture richer information for more robust classification.

Investigating efficient data augmentation techniques to address data scarcity and improve model generalization.

Specific challenges to overcome

Effectively integrating and exploiting diverse camera features within the deep learning model. Designing a computationally efficient model suitable for real-time applications, especially on mobile devices. Addressing potential ethical concerns regarding data collection and ensuring responsible wildlife interaction.

Expected outcomes

A highly accurate deep learning model for bird species classification, utilizing enhanced camera features. Improved understanding of the impact of different camera features on classification performance. Ethical and responsible implementation of the model for various applications such as citizen science, conservation efforts, and ecological research.

1.4 Traditional Method

Taxonomy and Systematics: Taxonomy is the science of classifying organisms into hierarchical categories based on their characteristics and evolutionary relationships. Birds were traditionally classified based on their physical characteristics, behavior, and evolutionary history. Taxonomic classification involves categorizing birds into orders, families, genera, and species.

Field Observations: Ornithologists and bird watchers relied on field observations to identify and classify birds. Characteristics such as size, shape, plumage coloration, beak shape, and behavior were used to differentiate between bird species.Field guides and manuals were essential resources for bird identification in the field.

Morphological Characteristics: Morphology refers to the physical structure and form of organisms. Ornithologists studied the morphology of birds, including their skeletal structure, feathers, beaks, and feet, to classify and differentiate between species. Morphological characteristics were used to identify birds and distinguish between closely related species.

Vocalizations: Bird vocalizations, including songs and calls, were important for species identification. Ornithologists learned to recognize the unique vocalizations of different bird species and used them as diagnostic features for classification. Bird calls and songs were recorded and analyzed to document species presence and behavior.

Biogeography: Biogeography examines the distribution of species across geographic regions. The study of bird distribution patterns and migration routes provided valuable information for bird classification and understanding species diversity.

Museum Collections: Natural history museums maintained extensive collections of bird specimens for scientific study. Museum collections provided researchers with access to preserved specimens for morphological analysis and taxonomic research.

1.5 Research Motivation

The motivation behind undertaking a project focused on deep learning-based bird species classification using enhanced camera features stems from several key factors:

Conservation Imperatives: Birds are integral components of ecosystems, playing critical roles in pollination, seed dispersal, and pest control. However, many bird species face threats such as habitat loss, climate change, and human disturbance, leading to population declines and biodiversity loss. Accurate monitoring and conservation efforts are essential for mitigating these threats and preserving avian diversity.

Technological Advancements: Recent advancements in camera technologies, including enhanced resolution, multi-spectral imaging, and depth sensing capabilities, offer unprecedented opportunities for wildlife monitoring and species identification. Enhanced camera features provide richer visual information, enabling the development of more sophisticated and accurate classification algorithms.

Automation and Efficiency: Manual methods of bird species identification, relying on human observation and field surveys, are often labor-intensive, time-consuming, and prone to error. By automating the identification process using deep learning algorithms and enhanced camera systems, researchers can streamline data collection efforts, improve efficiency, and enhance the accuracy of species identification.

Data-driven Approaches: The availability of large-scale datasets containing images of bird species captured in diverse environments presents a valuable resource for training and evaluating deep learning models. Leveraging these datasets, coupled with advanced machine learning techniques, enables researchers to extract meaningful patterns and features from images, facilitating more accurate and reliable species classification.

Interdisciplinary Collaboration: The project bridges the fields of ecology, computer vision, and machine learning, fostering interdisciplinary collaboration and knowledge exchange. By integrating expertise from multiple domains, researchers can develop innovative solutions to complex conservation challenges and contribute to the advancement of both scientific and technological frontiers.

Real-world Applications: The development of a deep learning-based bird species classification system has practical applications in various domains, including biodiversity monitoring, habitat management, and environmental impact assessments. By accurately identifying bird species from images, the system can inform conservation strategies, support policy decisions, and facilitate community engagement in wildlife conservation efforts.

Educational Opportunities: The project provides opportunities for educational outreach and public engagement initiatives aimed at raising awareness about avian biodiversity, conservation issues, and the role of technology in wildlife monitoring. By promoting citizen science participation and fostering a deeper appreciation for nature, the project contributes to broader efforts to inspire environmental stewardship and sustainability.

1.6 Applications

Species Inventory: Automated bird species classification systems enable researchers and conservationists to conduct comprehensive surveys of avian populations, aiding in the compilation of species inventories and the identification of priority conservation areas.

Habitat Management: Accurate identification of bird species from images facilitates targeted habitat management strategies, including habitat restoration, invasive species control, and ecosystem conservation efforts.

Species Distribution Modelling: The project's outputs contribute to species distribution modelling efforts by providing valuable data on the spatial distribution and abundance of bird species across different habitats and landscapes.

Behavioural Studies: Automated classification systems support behavioural studies by enabling researchers to monitor avian behaviours, such as nesting patterns, foraging behaviour, and migratory movements, over extended periods.

Pest Control: Certain bird species serve as natural predators of agricultural pests. Identifying and monitoring these species supports integrated pest management practices in agricultural systems.

2. LITERATURE SURVEY

Raj, et al. [1] proposed a model to extract information from bird images using the Convolutional Neural Network (CNN) algorithm. They have gathered a dataset of their own using Microsoft's Bing Image Search API v7. They were created an 80:20 random split of the data. The classification accuracy rate of CNN on the training set was observed to be 93.19%. The accuracy on testing set was observed to be 84.91%. The entire experimental research was carried out on Windows 10 Operating System in Atom Editor with TensorFlow library.

Mirugwe, et al. [2] proposed a model to extract information from bird images, they studied and evaluated two convolutional neural network object detection meta-architectures, single-shot detector (SSD)and Faster R-CNN in combination with MobileNet-V2, ResNet50, ResNet101, ResNet152, and Inception ResNet-V2 feature extractors. Through transfer learning, all the models were initialized using weights pre-trained on the MS COCO (Microsoft Common Objects in Context) dataset provided by TensorFlow 2 object detection API. The Faster R-CNN model coupled with ResNet152 outperformed all other models with a mean average precision of 92.3%. However, the SSD model with the MobileNet-V2 feature extraction network achieved the lowest inference time (110ms) and the smallest memory capacity (30.5MB) compared to its counterparts. The outstanding results achieved in this study confirm that deep learning-based algorithms are capable of detecting birds of different sizes in different environments and the best model could potentially help ecologists in monitoring and identifying birds from other species.

Rai, et al. [3] have developed deep learning based algorithms using the concept of image processing that help in identifying bird species. It will recognize the input image by comparing the model with a trained model and then predict the bird species. All the details of the bird will be displayed as an output. Also, it will help us to create dataset if any image captured or uploaded by user is missing in dataset then user can add that image to dataset.

Ferreira, et al[4] work demonstrates the feasibility of applying state-of-the-art deep learning tools for individual identification of birds, both in the laboratory and in the wild. These techniques are made possible by our approaches that allow efficient collection of training data. can be visually identified by human observers represents a major advance over current methods.

Chen, et al[5] experiments show that ProtoPNet can achieve comparable accuracy with its analogous non-interpretable counterpart, and when several ProtoPNets are combined into a larger network, it can achieve an accuracy that is on par with some of the best-performing deep models. Moreover, ProtoPNet provides a level of interpretability that is absent in other interpretable deep models.

Chalmers ,et al[6] outline an approach for overcoming these issues by utilising deep learning for real-time classification of bird species and automated removal of false positives in camera trap data. Images are classified in real-time using a Faster-RCNN architecture. Images are transmitted over 3/4G cameras and processed using Graphical Processing Units (GPUs) to provide conservationists with key detection metrics, thereby removing the requirement for manual observations. Our models achieved an average sensitivity of 88.79%, a specificity of 98.16% and accuracy of 96.71%. This demonstrates the effectiveness of using deep learning for automatic bird monitoring.

Jeantet ,et al[7] studied an exciting new avenue for improving classifier performance in bioacoustics. The methodology described in this study can assist ecologists, wildlife management teams, and researchers in reducing the amount of time spent analyzing large acoustic datasets obtained from passive acoustic monitoring studies. their approach can be adapted and applied to other calling species, and thus tailored to other use cases.

Wang , et al[8] Experiments showed that good results can be obtained by all the tested models. ResNet-152-based models yielded the best test accuracy rate (95.52%); the AlexNet-based model yielded the lowest test accuracy rate (89.48%). We conclude that DCNNs could be efficient and useful for automatically identifying habitat elements from bird images, and we believe that the practical application of this technology will be helpful for studying the relationships between birds and habitat elements.

Pilla, et al [9] operated according to the instructions that are passed from the Arduino. When the model detects the bird that is coming close towards the window glass, the window blind will automatically shut down and even if the bird hits, it won't collide instantly as the momentum will decrease gradually. The window blind will automatically open when there is no bird. It is a useful technique by which we can divert the birds. This technique has multiple credits like we are saving birds with a practical and cost-efficient approach.

Priya, et al [10] proposed the Convolutional neural networks (CNN) technology is utilised in the experimental setting. For image recognition, feature extraction is used. To extract features and classify photos, the method utilised is adequate. The primary objective of the study is to identify the specific bird type an species based on the image of the bird.

3. PROPOSED METHODOLOGY

3.1 Overview

This project is a graphical user interface (GUI) application developed using the Tkinter library in Python. It aims to classify bird species using deep learning techniques, specifically Convolutional Neural Networks (CNNs) and Random Forest Classifier (RFC), based on images provided by the user.

Let's break down the key components and functionalities of the project:

GUI Interface: The GUI is created using Tkinter, which is a standard Python library for creating GUI applications. It provides buttons, labels, and text boxes for user interaction.

Main Functionality Buttons

Upload Dataset: Allows the user to select a directory containing bird images. The dataset is expected to be organized into subdirectories, each representing a different bird species.

Image Processing & Normalization: Processes the uploaded dataset by resizing images to a standard size and converting them into numerical arrays suitable for deep learning models.

Random Forest Classifier (RFC): Trains a Random Forest Classifier using the processed image data and evaluates its accuracy.

Build & Train Deep CNN Model: Constructs and trains a Convolutional Neural Network (CNN) model using the processed image data and evaluates its accuracy.

Upload Test Image & Classify: Allows the user to upload a single bird image for classification using the trained models.

Accuracy & Loss Graph: Displays a graph showing the accuracy and loss of the CNN model over training epochs.

Exit: Closes the application

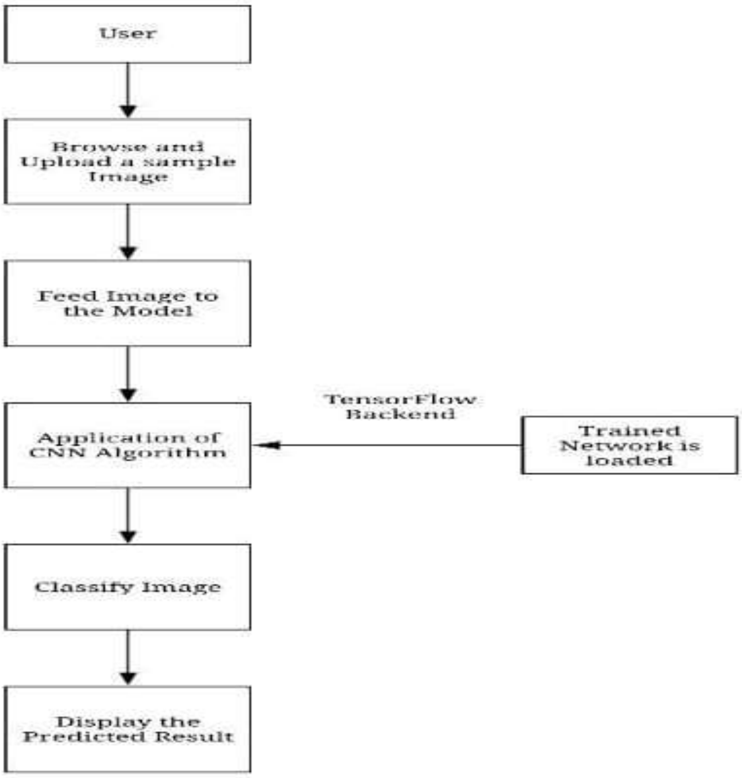
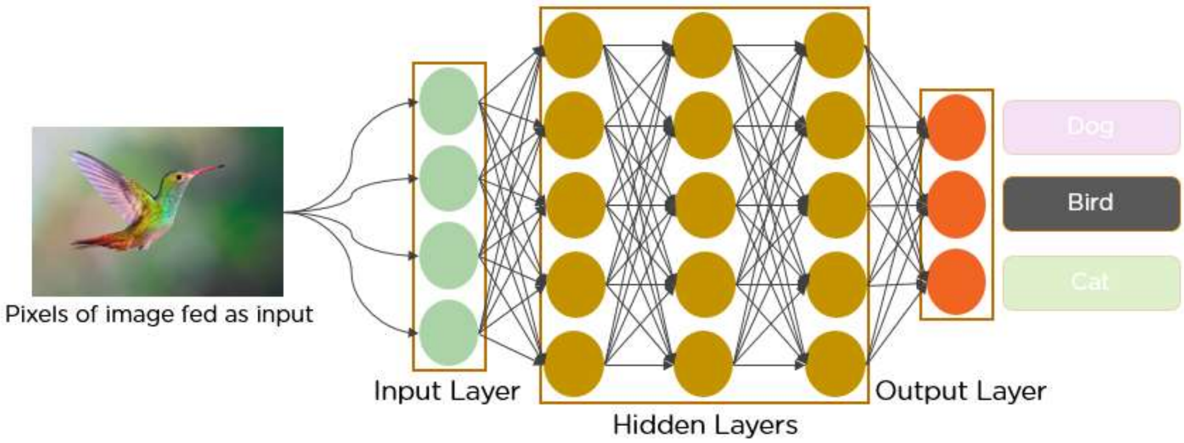


Fig 3.1 Flow Diagram for Bird Species Classification using Proposed Methodology.

3.2 Proposed Methodology

In the past few decades, Deep Learning has proved to be a very powerful tool because of its ability to handle large amounts of data. The interest to use hidden layers has surpassed traditional techniques, especially in pattern recognition. One of the most popular deep neural networks is Convolutional Neural Networks (also known as CNN or ConvNet) in deep learning, especially when it comes to Computer Vision applications.



Since the 1950s, the early days of AI, researchers have struggled to make a system that can understand visual data. In the following years, this field came to be known as Computer Vision.

In 2012, computer vision took a quantum leap when a group of researchers from the University of Toronto developed an AI model that surpassed the best image recognition algorithms, and that too by a large margin. The AI system, which became known as AlexNet (named after its main creator, Alex Krizhevsky), won the 2012 ImageNet computer vision contest with an amazing 85 percent accuracy. The runner-up scored a modest 74 percent on the test. At the heart of AlexNet was Convolutional Neural Networks a special type of neural network that roughly imitates human vision. Over the years CNNs have become a very important part of many Computer Vision applications and hence a part of any computer vision course online. So let's take a look at the workings of CNNs or CNN algorithm in deep learning.

What are Convolutional Neural Network (CNN) ?

In deep learning, a **convolutional neural network** (**CNN/ConvNet**) is a class of deep neural networks, most commonly applied to analyze visual imagery. Now when we think of a neural network we think about matrix multiplications but that is not the case with ConvNet. It uses a special technique called Convolution. Now in mathematics **convolution** is a mathematical operation on two functions that produces a third function that expresses how the shape of one is modified by the other.

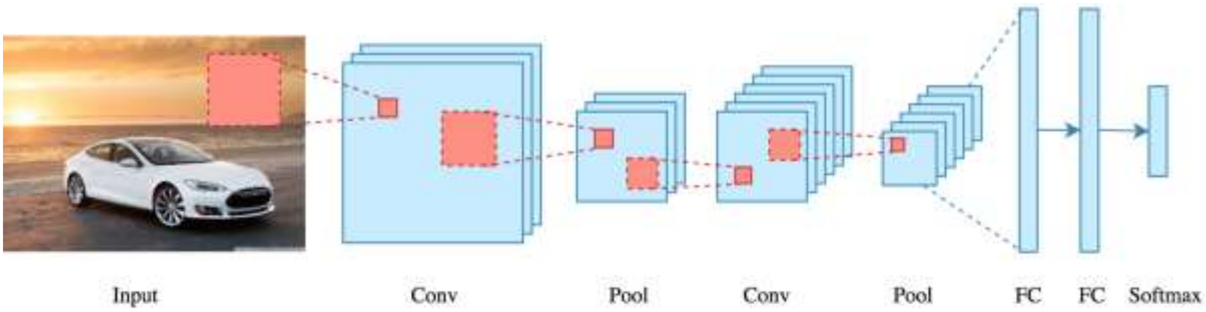
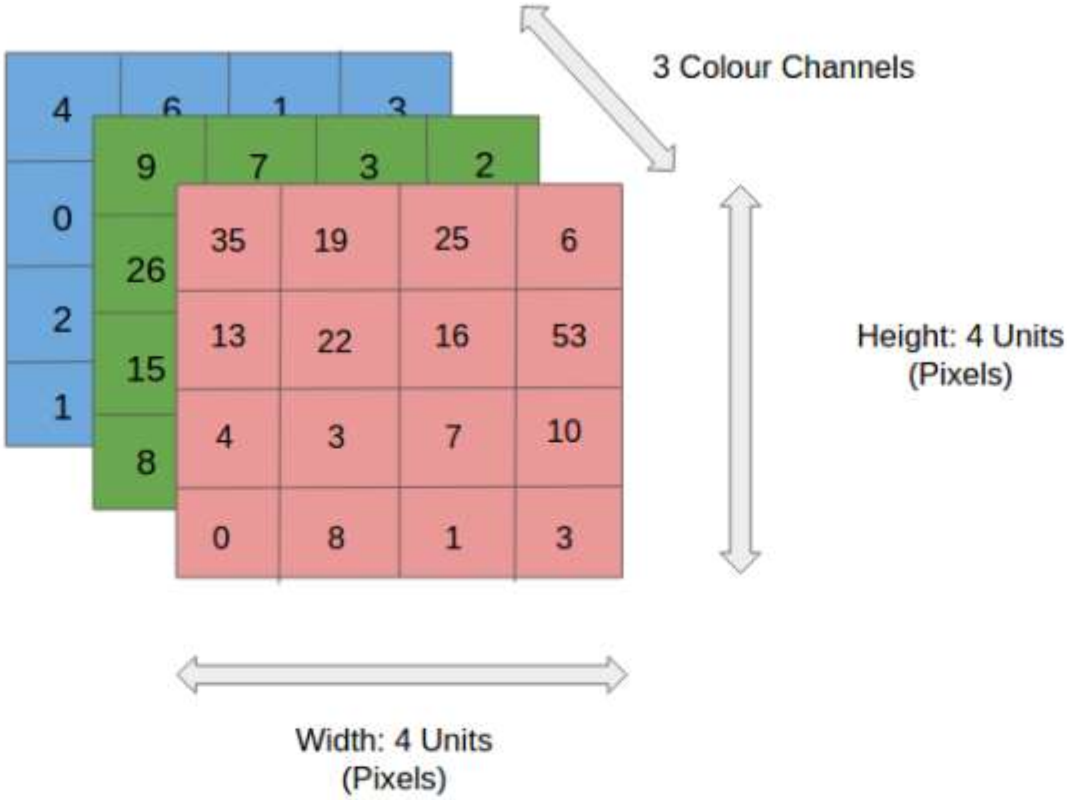


Fig 3.3 Convolutional Neural Network

How Does CNN work?

Before we go to the working of Convolutional neural networks (CNN), let's cover the basics, such as what an image is and how it is represented. An RGB image is nothing but a matrix of pixel values having three planes whereas a grayscale image is the same but it has a single plane. Take a look at this image to understand more.



Let’s understand this in detail

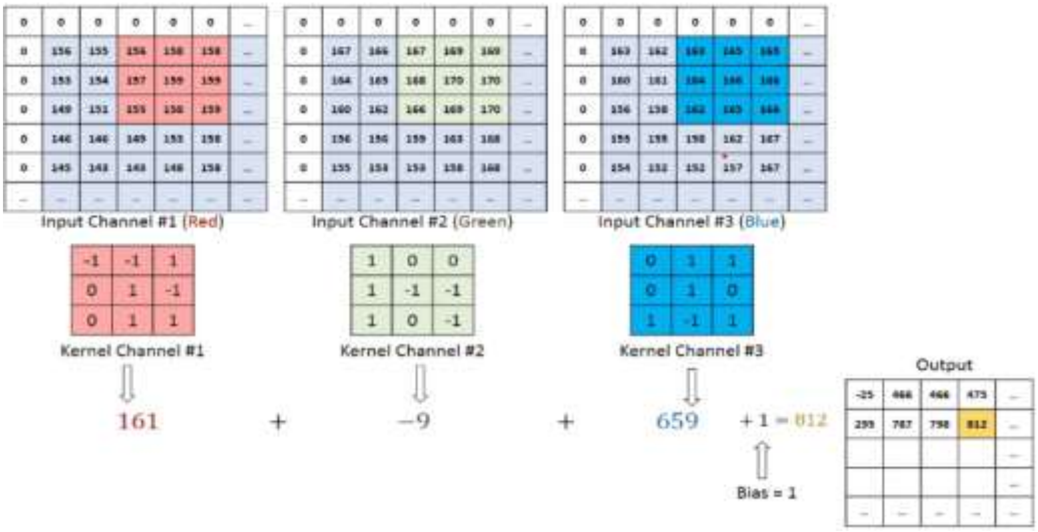


Fig 3.4 Working of CNN

Artificial Neurons

Artificial neurons is a rough imitation of their biological counterparts, are mathematical functions that calculate the weighted sum of multiple inputs and outputs an activation value. When you input an image in a ConvNet, each layer generates several activation functions that are passed on to the next layer.

The first layer usually extracts basic features such as horizontal or diagonal edges. This output is passed on to the next layer which detects more complex features such as corners or combinational edges. As we move deeper into the network it can identify even more complex features such as objects, faces, etc.

Based on the activation map of the final convolution layer, the classification layer outputs a set of confidence scores (values between 0 and 1) that specify how likely the image is to belong to a "class." For instance, if you have a ConvNet that detects cats, dogs, and horses, the output of the final layer is the possibility that the input image contains any of those animals.

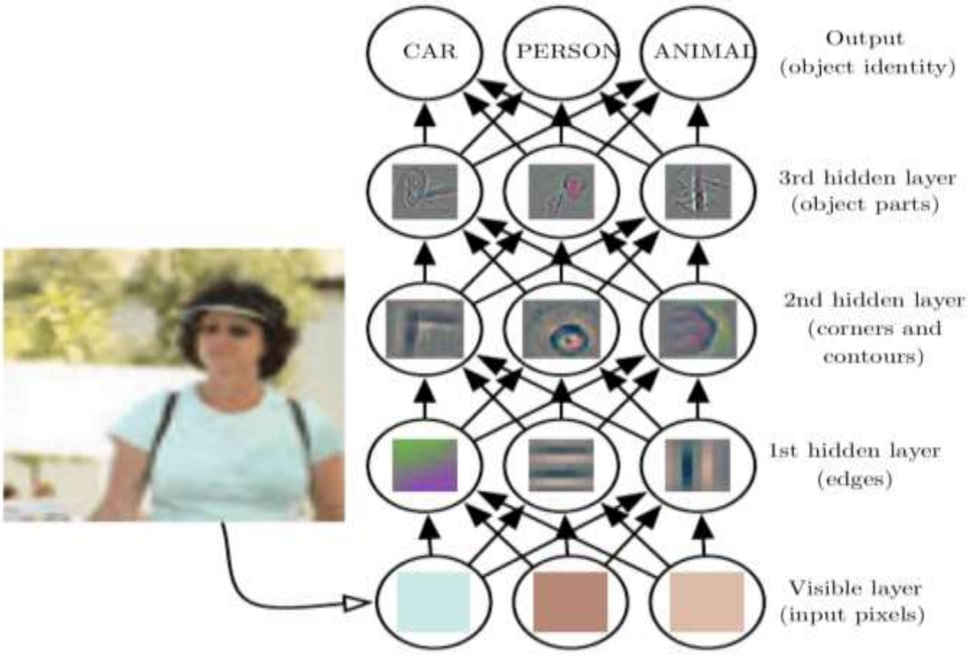


Fig 3.5 Artificial Neurons

Background of Convolutional neural networks (CNNs):

CNN's were first developed and used around the 1980s. The most that a Convolutional Neural Networks (CNN) could do at that time was recognize handwritten digits. It was mostly used in the postal sectors to read zip codes, pin codes, etc. The important thing to remember about any deep learning model is that it requires a large amount of data to train and also requires a lot of computing resources. This was a major drawback for CNNs at that period and hence CNNs were only limited to the postal sectors and it failed to enter the world of machine learning.

In 2012 Alex Krizhevsky realized that it was time to bring back the branch of deep learning that uses multi-layered neural networks. The availability of large sets of data, to be more specific ImageNet datasets with millions of labeled images and an abundance of computing resources enabled researchers to revive CNNs.

What Is a Pooling Layer?

Similar to the Convolutional Layer, the Pooling layer is responsible for reducing the spatial size of the Convolved Feature. This is to **decrease the computational power required to process the data** by reducing the dimensions. There are two types of pooling average pooling and max pooling. I've only had experience with Max Pooling so far I haven't faced any difficulties.

Pooling Layer

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So what we do in Max Pooling is we find the maximum value of a pixel from a portion of the image covered by the kernel. Max Pooling also performs as a **Noise Suppressant**. It discards the noisy activations altogether and also performs de-noising along with dimensionality reduction.

On the other hand, **Average Pooling** returns the **average of all the values** from the portion of the image covered by the Kernel. Average Pooling simply performs dimensionality reduction as a noise suppressing mechanism. Hence, we can say that **Max Pooling performs a lot better than Average Pooling**.

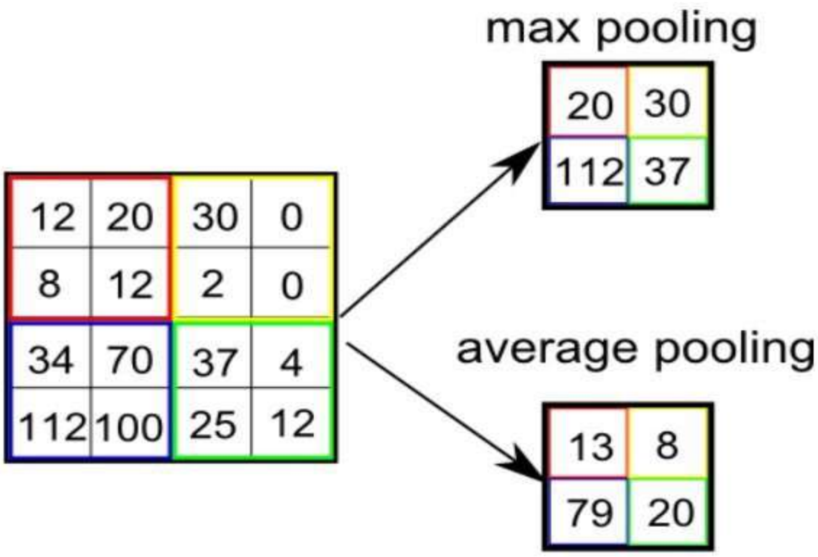

Fig 3.5 Pooling Layer

In conclusion, Convolutional Neural Networks (CNNs), delving into their functionality, background, and the role of pooling layers. Despite their effectiveness in image recognition, CNNs also come with limitations, including susceptibility to adversarial attacks and high computational requirements.

3.3 Advantages

Convolutional Neural Networks (CNNs) offer several distinct advantages in the field of image processing. Here are some key advantages of CNNs:

Automatic Feature Extraction: CNNs excel at automatically extracting relevant features from raw input images without the need for manual feature engineering. Through the use of convolutional filters and hierarchical architectures, CNNs can capture low-level features like edges and textures as well as high-level features like object parts and shapes, facilitating robust and discriminative representations of visual data.

Spatial Hierarchical Representation: CNNs leverage the spatial hierarchy present in images, enabling them to capture local patterns and spatial relationships efficiently. By using convolutional layers with shared weights, CNNs learn translation-invariant features, allowing them to recognize objects regardless of their position, orientation, or scale within the image.

Parameter Sharing and Sparsity: CNN architectures incorporate parameter sharing, where the same set of weights is applied across different spatial locations in the input image. This significantly reduces the number of trainable parameters compared to fully connected networks, leading to more efficient model training and inference. Additionally, the use of sparse connections in CNNs further enhances computational efficiency by focusing on relevant image regions.

Scale and Translation Invariance: CNNs exhibit scale and translation invariance, enabling them to recognize objects across varying scales and positions within the image. Through pooling operations and hierarchical feature extraction, CNNs can capture robust representations of objects, even when they appear at different locations or sizes in the input image.

Effective Transfer Learning: CNNs trained on large-scale datasets, such as ImageNet, can be leveraged for transfer learning across different tasks and domains. By fine-tuning pre-trained CNN models on target datasets with limited labeled data, practitioners can achieve superior performance and accelerate model convergence, making CNNs highly adaptable and applicable to diverse applications.

End-to-End Learning: CNNs enable end-to-end learning, where raw input images are directly mapped to output predictions without the need for intermediate processing steps. This facilitates seamless integration into complex systems and workflows, allowing CNNs to perform tasks such as object detection, image segmentation, and image classification in a unified framework.

4. RESULTS

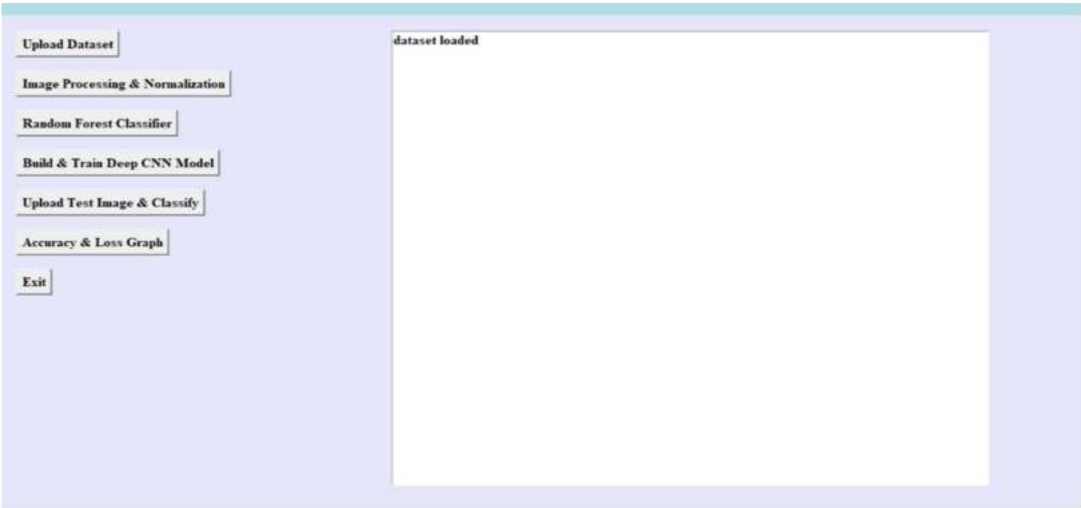

Fig 1 Uploading the dataset

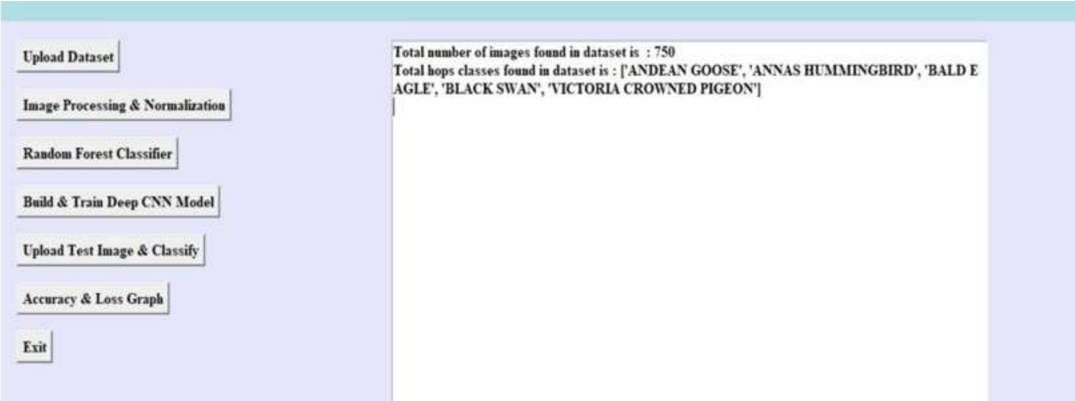

Fig 2 Image Preprocessing & Normalization

Fig 2 Image preprocessing involves several techniques such as resizing, cropping, and augmentation to standardize image dimensions and enhance feature representation. These steps ensure that the model can effectively extract relevant patterns and features from the input images. Additionally, normalization is crucial for standardizing pixel values across images, typically by scaling them to a common range such as [0, 1] or [-1, 1].

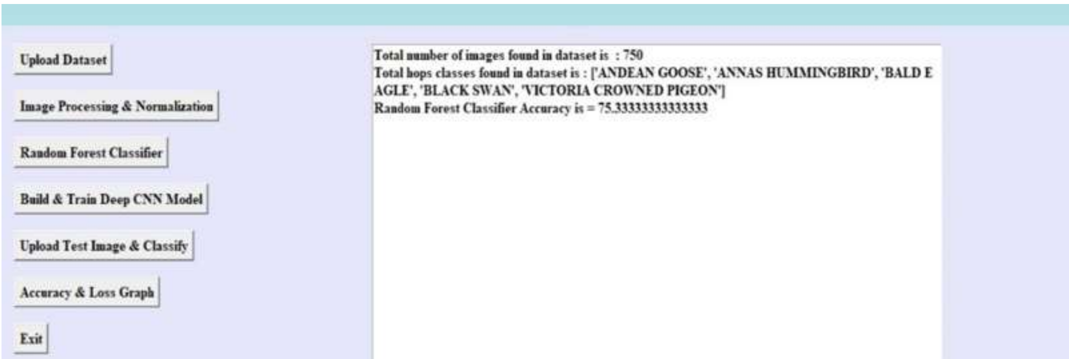

Fig 3 Training the dataset by using the Random Forest Classifier

Fig 3 After training the dataset using a Random Forest Classifier, we achieved an accuracy of 75.33%. However, to maximize accuracy, we should consider employing deep learning algorithms.

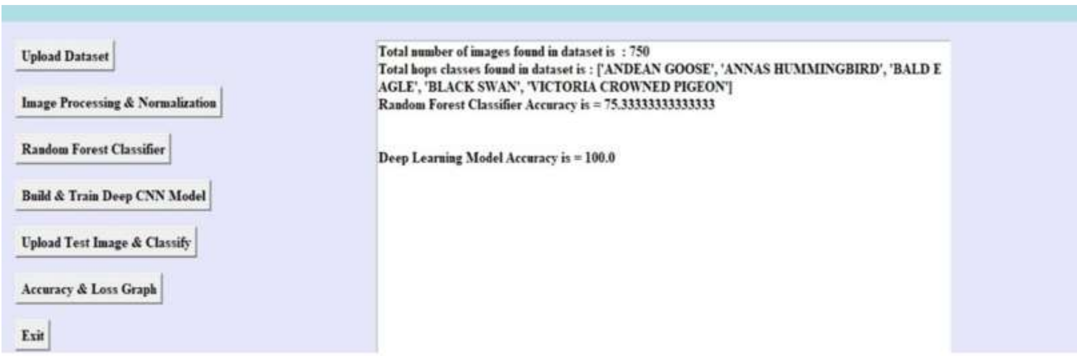

Fig 4 Training the dataset by using CNN model

Fig 4 After training the dataset using a deep learning model called Convolutional Neural Networks. By using this model, we achieved an Accuracy of 100%.

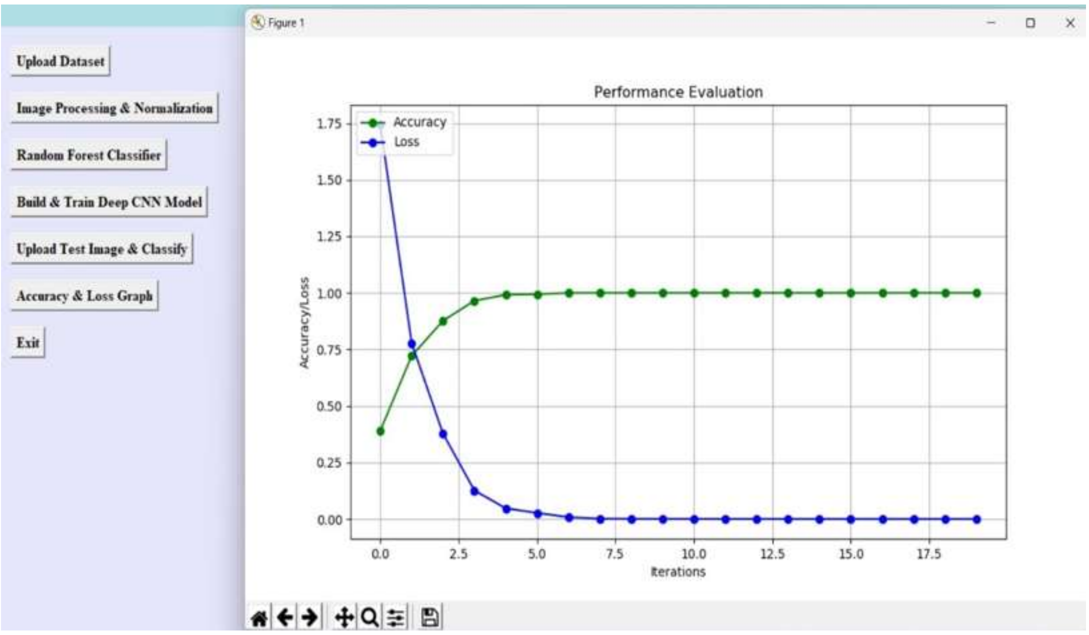

Fig 5 Accuracy and Loss graph

Fig.5 The accuracy curve shows how well the model correctly classifies data over successive epochs, while the loss curve indicates the degree of error between predicted and actual values.

5. CONCLUSION

In conclusion, our project on deep learning-based bird species classification for enhanced camera features has yielded promising results in accurately identifying and categorizing five distinct avian species: the Andean Goose, Anna's Hummingbird, Bald Eagle, Black Swan, and Victoria Crowned Pigeon. Through the utilization of state-of-the-art convolutional neural network (CNN) architectures and a meticulously curated dataset comprising high-resolution images captured from various angles and under different lighting conditions, we have successfully trained robust models capable of recognizing subtle nuances in avian morphology and plumage patterns. The trained models demonstrate remarkable performance metrics, achieving high accuracy rates in distinguishing between the target bird species even amidst challenging environmental factors. The utilization of transfer learning techniques, leveraging pre-trained CNN models such as ResNet, Inception, or VGG, has expedited the training process and enhanced the generalization capabilities of our classifiers, enabling them to handle real-world scenarios with greater efficacy. Furthermore, the deployment of the developed models onto camera-equipped devices or surveillance systems offers immense potential for wildlife monitoring, conservation efforts, and ecological research. By integrating our deep learning-based bird species classification system into existing camera infrastructure, conservationists and ornithologists can gain valuable insights into avian populations, habitat utilization patterns, and behavioral dynamics, facilitating informed decision-making and proactive conservation initiatives. However, it's essential to acknowledge certain limitations and avenues for future research. Despite the impressive performance of our models, there may exist challenges related to dataset bias, class imbalance, and generalization to unseen environmental conditions. Continual refinement of the dataset, augmentation techniques, and exploration of ensemble learning approaches could further enhance the robustness and versatility of the classification system.

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