IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Impact Factor 8.066 ⫘ Peer-reviewed & Refereed journal ⫘ Vol. 12, Issue 5, May 2025

DOI: 10.17148/IARJSET.2025.12579

Birds Classification and Identification using Machine Learning Techniques, Particularly with Image Datasets

Dharmaraj K B [1], Poorvika Krishna [2], Sinchan M [3], Prajwal [4], Sagar S [5]

Assistant Professor, Department of ISE, MITM, Mysore, VTU Belagavi, India[1]

UG Students, Department of ISE, MITM, Mysore, VTU Belagavi, India[2-5]

Abstract: Identifying bird species from images presents a considerable challenge due to the subtle differences between species and the significant variability within species. Although bird species may share similar anatomical characteristics, they can vary greatly in terms of color, shape, and posture. Additional factors such as differing lighting conditions, intricate backgrounds, and various poses—like birds in flight, swimming, or partially hidden while perched—complicate the classification process. Even seasoned ornithologists may encounter ambiguity in species identification based solely on visual information. This study introduces a machine learning-based method designed to assist novice bird watchers in accurately identifying bird species from their photographs. By utilizing image classification models that have been trained on labelled bird datasets, the proposed system is capable of recognizing unique visual patterns and features, thereby offering a scalable and intelligent solution for ornithological identification. This method not only enhances public interest in biodiversity but also aids citizen science and conservation initiatives through the use of artificial intelligence.

Keywords: Birds Identification

I. INTRODUCTION

Birds are essential for sustaining ecological equilibrium, acting as indicators of environmental well-being and enhancing biodiversity. The practice of bird watching, both as a scientific endeavor and a leisure activity, has seen a rise in popularity globally. Nevertheless, distinguishing bird species through visual observation poses a significant challenge, even for seasoned ornithologists. Minor variations in plumage, size, and shape, along with factors such as differing light conditions, varied backgrounds, and the dynamic nature of bird poses, render species classification exceedingly intricate. This complexity is further intensified by the existence of numerous species with overlapping traits and seasonal changes in their appearance. Conventional identification techniques heavily depend on field guides and expert knowledge, which may not always be readily available to amateur bird watchers or citizen scientists. The proliferation of digital cameras and smartphones has led to the capture of an extensive array of bird images. every day, creating an opportunity to automate the identification process using machine learning techniques.

Machine learning, especially deep learning architectures such as convolutional neural networks (CNNs), has demonstrated significant effectiveness in image classification applications. These models are capable of learning and identifying important visual patterns from extensive datasets, rendering them particularly effective for recognizing bird species. Through training on labeled datasets of bird images, machine learning algorithms can attain high levels of accuracy in species identification, even when faced with noise and obstructions.

The aim of this study is to create a machine learning-driven system that aids novice bird watchers in recognizing bird species from the photographs they take. This proposed system seeks to connect professional ornithological resources with casual birding, facilitating precise identification and promoting public involvement in biodiversity observation and conservation efforts.

II. PROPOSED SYSTEM

Identifying bird species poses considerable difficulties owing to differences in their physical characteristics, varying lighting conditions, and intricate natural environments. To tackle these challenges, the suggested system utilizes deep learning methodologies, particularly the EfficientNet-B3 framework, to improve classification precision and scalability.

DOI: 10.17148/IARJSET.2025.12579

Model Architecture and Accuracy: In contrast to conventional models like VGG16, which attained approximately 80% accuracy, the proposed system employs EfficientNet-B3, resulting in enhanced accuracy surpassing 90% and facilitating the identification of as many as 325 bird species. This improvement is realized through effective scaling and optimized use of parameters within the model's architecture.

Image Preprocessing: Prior to classification, images of birds are subjected to preprocessing procedures that encompass noise reduction and data augmentation techniques, including rotation, flipping, and scaling, aimed at enhancing the model's generalization and resilience to variations in the environment.

Training and Implementation: The system has been developed utilizing Python, with TensorFlow and Keras as the main frameworks for deep learning. The model is trained on an extensive, annotated dataset of bird species to guarantee optimal performance and adaptability across various species and imaging conditions.

Deployment: In order to enhance accessibility, the trained model is implemented as an intuitive web application, enabling users to upload images of birds and obtain immediate species predictions. The interface is tailored for researchers, bird enthusiasts, and conservationists who possess limited technical expertise.

Scalability and Future Enhancements: The system is designed for scalability, with possible improvements such as the creation of a mobile application, cloud storage for data and model hosting, and real-time video-based bird detection, thereby increasing the platform's applicability in both fieldwork and research settings.

Image Preprocessing: The input images are processed through a preprocessing pipeline that encompasses noise reduction, conversion to grayscale, and data augmentation techniques such as rotation, zooming, and flipping. This process guarantees uniform input quality and enhances the variety of training data, thereby improving the model's ability to generalize. Additionally, the images are resized to conform to the input dimensions specified by the classification model.

Algorithm: The system employs a blend of deep learning techniques and image preprocessing tools to accurately identify various bird species. The following is a summary of the components of the algorithm:

OpenCV Integration: The OpenCV (Open Source Computer Vision Library) is utilized for image preprocessing prior to inputting data into the classification model. This process involves enhancing contrast to ensure that text is distinctly visible against the background, even in varying lighting conditions.

Grayscale Conversion: Transforms RGB images into grayscale to minimize computational demands while maintaining structural integrity. Noise Reduction: Employs Gaussian blur and median filtering techniques to eliminate background noise. Image Normalization and Resizing: Standardizes all images to a uniform size (e.g., 300x300 pixels) to ensure compatibility for input.

Deep Learning Classification (EfficientNet-B3): In order to achieve precise classification of bird species, the proposed system utilizes EfficientNet-B3, a deep learning model recognized for its excellent balance of accuracy and computational efficiency. EfficientNet-B3 incorporates a series of convolutional layers that autonomously learn the spatial hierarchies of features from input bird images. These features encompass texture, shape, color patterns, and other visual indicators that are crucial for differentiating between bird species. The model is initialized with pre-trained weights from ImageNet, a comprehensive image dataset, enabling the system to utilize pre-existing feature knowledge. This approach, referred to as transfer learning, significantly decreases training duration and enhances performance, even when working with a relatively smaller, domain-specific dataset.

Deployment: The developed model is incorporated into a web application created with Flask or Streamlit, enabling accessibility for users with limited technical expertise. The web interface facilitates the uploading of bird images for immediate identification. Once an image is uploaded, it is analyzed, and the model determines the bird species, providing pertinent details such as the scientific name and confidence level. The design emphasizes simplicity, responsiveness, and user-friendliness to guarantee an effective user experience.

Post-processing and Output: The developed model is incorporated into a web-based application created with Flask or Streamlit, allowing users with limited technical expertise to access it. The web interface enables users to upload images of birds for immediate identification. After an image is uploaded, it is analyzed, and the model determines the bird species, providing pertinent details such as the scientific name and confidence level.

DOI: 10.17148/IARJSET.2025.12579

The design prioritizes simplicity, responsiveness, and user-friendliness to facilitate an effective user experience. Following classification, post-processing techniques are employed to improve the clarity and reliability of the output. A confidence threshold (for instance, 85%) is implemented to exclude uncertain predictions, ensuring that only results with high confidence are shown to the user. Subsequently, label mapping is utilized to translate internal class identifiers into understandable bird species names. The final output is delivered in a detailed format, which may include not just the species name but also a corresponding image, audio recording (if available), and a brief biological description. This methodology enhances the system's educational and practical significance for bird enthusiasts, researchers, and conservationists.

III. LITERATURE SURVEY

The classification and identification of birds have become essential fields in computer vision and biodiversity informatics. Researchers have utilized a range of machine learning and deep learning techniques to address the challenges of bird recognition, which arise from differences in pose, lighting, background, and occlusion.

Survey of Existing Approaches:

Penchala Abhinav [1] The bird sound classification system follows a structured process, beginning with data collection. Bird sound recordings are gathered from the BirdClef-2024 dataset, providing a diverse set of bird calls for training and testing. Next, the preprocessing stage ensures consistency by cleaning the recordings, adjusting them to the same length and quality, and removing background noise. Once the audio is standardized, feature extraction is performed using Mel-Frequency Cepstral Coefficients (MFCCs), which help capture essential sound patterns unique to different bird species. storage, making it less suitable for embedded systems or low resource environments. After extracting features, the system proceeds with model training, where it learns to classify bird species using K-Nearest Neighbors (KNN), Random Forest, and Support Vector Machine (SVM) models

Deepadarsini K T. [2] presented a conceptual model Managing parking efficiently has become a growing challenge due to the increasing number of vehicles and the limitations of traditional parking systems. Conventional methods often struggle with space allocation, security monitoring, and vehicle tracking, leading to inefficiencies. This study proposes a smart parking system using Automatic License Plate Recognition (ALPR) integrated with Raspberry Pi and Optical Character Recognition (OCR) techniques to automate vehicle identification. By reducing manual intervention and optimizing space utilization, the system improves overall parking management efficiency. The system is built around a Raspberry Pi-based platform, which serves as the processing unit for license plate detection. A camera module captures real-time images of incoming and outgoing vehicles, while an infrared (IR) sensor detects entry and exit, ensuring accurate vehicle tracking. The captured images are processed using OpenCV for plate localization, followed by OCR-based text extraction to identify vehicle details. The recognized plate numbers are stored in a cloud-based relational database, enabling efficient parking management and real-time security monitoring.

Dr. S. Hemalatha [3] The system for identifying bird species is built using a type of deep learning model called a Convolutional Neural Network (CNN). This model can analyze bird images and recognize different species by learning patterns such as feather colors, beak shapes, and body structures. The system is trained using well-known bird image datasets like CUB200-2011, Birdsnap, and Kaggle's species dataset The CNN model consists of several layers. The first layers focus on detecting simple patterns like edges and colors, while the deeper layers identify more complex details that differentiate one bird species from another. A fully connected layer at the end of the network helps in classifying the images into different bird species. To improve accuracy, the system uses a technique called transfer learning, where an already trained model like ResNet or VGG-16 is fine-tuned with bird images. This helps the model learn faster and perform better, especially when the dataset is small.

Mahsa Mohaghegh [4] The bird sound classification system follows a structured approach, beginning with data collection, where bird sound recordings are gathered from a dataset containing various species. Once the data is collected, the preprocessing stage ensures high-quality input by removing background noise and converting the audio into a standardized format. The next step is feature extraction, where key sound characteristics, such as Mel-Frequency Cepstral Coefficients (MFCCs) and Spectrograms are examined to identify distinct patterns in avian vocalizations. Following the extraction of features, the process advances to model training, during which various machine learning models, such as Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and Artificial Neural Networks (ANNs), are trained to differentiate between bird species. Upon completion of the training phase, the most effective model is chosen for prediction and classification, enabling the system to recognize bird species from new audio samples. Ultimately, a user-friendly interface is created, allowing users to upload recordings of bird sounds and receive automated predictions, thereby facilitating bird identification for researchers, bird enthusiasts, and conservationists.

IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Impact Factor 8.066 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 12, Issue 5, May 2025

DOI: 10.17148/IARJSET.2025.12579

Comparative Analysis and Motivation: The analyzed research suggests that although deep learning methods provide significant accuracy in classifying bird species, they generally necessitate extensive datasets and substantial computational power, which restricts their use on mobile or embedded systems. Audio-based models utilizing MFCCs demonstrate effectiveness but frequently underperform in noisy outdoor settings. Systems that concentrate exclusively on either image or audio data face challenges with inconsistent performance in fluctuating environmental conditions, including inadequate lighting, background interference, or low-quality recordings.

Inspired by these insights, the system proposed in this paper seeks to achieve a balance between classification accuracy and computational efficiency. Rather than depending solely on intricate, resource-demanding models, the system utilizes moderately deep CNNs for image classification and MFCC-based techniques for audio analysis. This strategy guarantees:

• Low computational cost, making it appropriate for resource-limited environments and edge devices.
• Quick and precise predictions, facilitating prompt bird identification in both field and laboratory settings.
• Ease of use and scalability, enabling straightforward integration into research tools, mobile applications, or citizen science initiatives.

IV. BLOCK DIAGRAM AND SYSTEM ARCHITECTURE

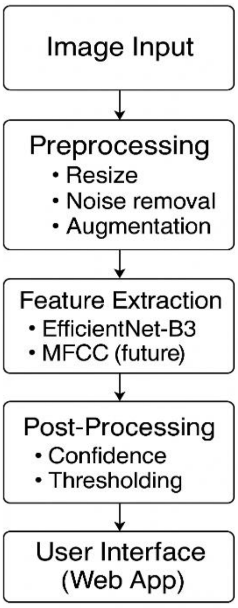

Fig. 1. Block Diagram

1. **Image Input:** The system is designed to accept images of birds, which can be captured via a camera or uploaded by users. These images serve as the primary data source for identifying various species.

2. **Pre-processing Module:** The input images are subjected to a pre-processing phase aimed at enhancing their quality and uniformity. This process involves resizing, normalization, and noise reduction techniques to ensure they are compatible with the deep learning model, thereby improving recognition accuracy.

3. **Feature Extraction:** The system utilizes EfficientNet-B3, a pre-trained deep convolutional neural network, to automatically extract both spatial and texture-based features from the bird images. These features are crucial for distinguishing between bird species based on visual characteristics such as color, shape, and plumage.

4. **Classification Module**: The features extracted are then processed through fully connected layers within the EfficientNet-B3 model. The final output layer employs softmax activation to assign probabilities to each species class, with the class exhibiting the highest probability being identified as the predicted bird species.

5. **Post-processing and Label Mapping**: Following the prediction phase, internal class indices are translated into easily understandable bird names. Predictions that fall below a specified confidence threshold (for instance, 85%) are excluded to maintain reliability. The ultimate results comprise the bird's name, its scientific classification, and the associated confidence score.

IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology
Impact Factor 8.066 ⁘ Peer-reviewed & Refereed journal ⁘ Vol. 12, Issue 5, May 2025
DOI: 10.17148/IARJSET.2025.12579

6. **Output Interface:** The system displays results via an intuitive web interface developed using Flask or Streamlit. Users are able to view the identified species alongside visual representations, concise descriptions, and supplementary information (including taxonomy). The interface is designed to accommodate future enhancements such as database logging or mobile application deployment.

V. IMPLEMENTATION DETAILS

The bird classification and identification system is developed using Python as the primary programming language, incorporating advanced deep learning libraries to achieve precise and efficient species identification.

This system is structured to be scalable, user-friendly, and suitable for both research and field applications. The development phase commences with the assembly of a dataset comprising images of 325 bird species, which is segmented into training, validation, and testing sets to facilitate accurate model assessment. Various preprocessing methods, including image resizing, normalization, and data augmentation techniques such as rotation, flipping, and zooming, are employed to bolster the model's robustness and generalization capabilities.

For the classification process, the EfficientNet-B3 model is selected for its ideal balance of computational efficiency and accuracy. This model utilizes a series of convolutional layers to automatically extract spatial features from bird images. To enhance training speed and accuracy, transfer learning is applied by initializing the model with weights pre-trained on the ImageNet dataset, followed by fine-tuning on the bird-specific dataset to tailor it for the classification task. The training process employs the Adam optimizer and categorical cross-entropy as the loss function, which is appropriate for multi-class classification challenges. Model performance is evaluated using accuracy, precision, and recall metrics. Training occurs on a GPU-enabled system to accelerate the learning process, with early stopping and learning rate scheduling implemented to mitigate overfitting and optimize convergence.

After the model reaches an acceptable level of performance, it is implemented as a web application utilizing Flask or Streamlit. This deployment interface enables users to upload images of birds and obtain immediate identification results. The output comprises the predicted species name, confidence score, scientific classification, and, if desired, supplementary information such as habitat or conservation status.

Additionally, the system architecture is structured to accommodate future improvements, including integration with cloud storage for data management, deployment on mobile devices via TensorFlow Lite, and real-time detection through cameras for field research purposes. These functionalities are intended to enhance accessibility and usability for bird watchers, researchers, and conservationists.

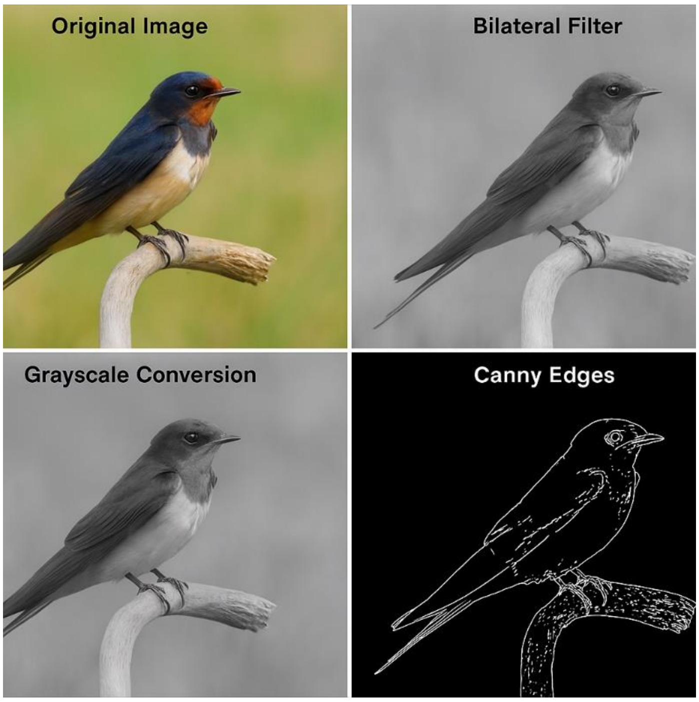

Fig. 2. Pre-processing Images

IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Impact Factor 8.066 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 12, Issue 5, May 2025

DOI: 10.17148/IARJSET.2025.12579

VI. RESULT AND PERFORMANCE ANALYSIS

The suggested system for bird classification and identification produced encouraging outcomes regarding accuracy and efficiency. Utilizing the EfficientNet-B3 architecture, the system markedly enhanced classification performance compared to conventional convolutional neural networks like VGG16. The model underwent training and evaluation on a dataset containing 325 unique bird species, showcasing a significant improvement in predictive reliability.

In the assessment phase, the model demonstrated a classification accuracy exceeding 90%, representing a significant enhancement compared to previous techniques that typically achieved around 80%. This improved performance is credited to the EfficientNet-B3 model's refined scaling of depth, width, and resolution, which enables it to extract more relevant features while utilizing fewer computational resources.

The system's resilience was confirmed through evaluations on images taken under diverse lighting conditions and backgrounds. Thanks to preprocessing methods including grayscale conversion, noise reduction via Gaussian and bilateral filters, and data augmentation strategies, the model consistently upheld high accuracy across a range of inputs.

Additionally, the system exhibited impressive precision and recall metrics, indicating its capability to reliably and accurately identify various bird species. The model's inference speed, averaging less than one second per image, further confirms its appropriateness for real-time applications. To improve user accessibility, the trained model was made available as a web-based application. This platform enables users to upload images of birds and promptly receive identification results, including the species name, classification confidence, and supplementary biological details.

The intuitive design facilitates wider adoption among both researchers and birdwatching enthusiasts. For OCR recognition, the cropped plate image was processed using Tesseract OCR via the pytesseract interface. Tesseract, utilizing its default English language model, employed a Long Short Term Memory (LSTM) based neural network for text processing. Under ideal conditions, it achieved a recognition accuracy ranging from 92% to 94%. However, in more difficult situations involving blurred characters, poor lighting, or skewed text, the accuracy decreased to approximately 85%, primarily due to misclassified or partially recognized characters.

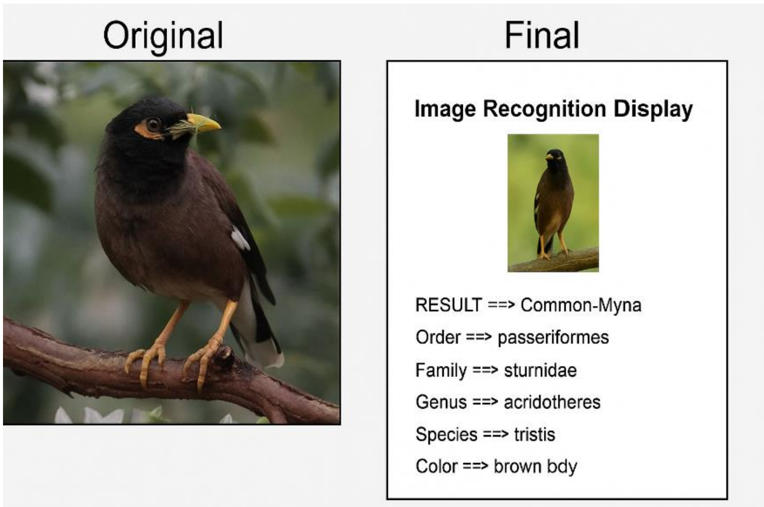

Fig 3. Original and Final Image

VII. CHALLENGES AND LIMITATIONS

The system for classifying and identifying birds, while providing notable benefits in automation and precision, encounters several intrinsic challenges and limitations. A primary concern stems from the significant variability in environmental conditions under which bird images are taken. Natural fluctuations in lighting, background distractions, bird postures, and partial obstructions frequently impair the model's performance.

These external influences complicate the task for even sophisticated deep learning models to reliably identify species with a high degree of accuracy. Another significant drawback is the visual resemblance among various bird species.

Numerous birds, particularly those belonging to the same family or genus, exhibit strikingly similar color patterns, shapes, and sizes, which heightens the risk of misclassification. The system is also heavily reliant on the quality and diversity of the training dataset.

If the dataset is deficient in samples of specific species or fails to encompass a broad spectrum of environmental conditions, the trained model may struggle to generalize effectively to real-world situations. Moreover, the accuracy of classification is significantly influenced by the clarity and resolution of the input images. Blurry, low-resolution, or poorly illuminated images often result in erroneous predictions. This issue becomes especially critical when the system is utilized in real-time or mobile applications, where image quality can vary considerably.

From a technical perspective, despite the effectiveness of models such as EfficientNet-B3, deep learning necessitates considerable computational resources during both the training and inference stages. This requirement poses challenges for deploying the model on low-power devices or in settings with limited processing capabilities. Additionally, there is frequently a delay in processing images, particularly when pre-processing, feature extraction, and classification are executed sequentially, which can impede the system's real-time performance.

The presence of class imbalance within the dataset is a significant factor that can negatively impact the accuracy of the model. When certain bird species are underrepresented, the model is inclined to prioritize the more prevalent classes, which diminishes its capacity to accurately recognize rarer species. Additionally, the existing system is exclusively dependent on visual data. In contrast to human experts who can utilize auditory signals, flight patterns, or environmental context to assist in identification, the system does not have access to such multimodal information, which could greatly improve the reliability of classification.

VIII. CONCLUSION

In summary, the proposed system for bird classification and identification illustrates the efficacy of deep learning models, especially EfficientNet-B3, in accurately identifying bird species from images. Through meticulous preprocessing, data augmentation, and transfer learning, the system achieves impressive classification accuracy, surpassing traditional models like VGG16. Its implementation as a user-friendly web application improves accessibility for bird watchers, researchers, and conservationists, facilitating real-time identification of over 300 species with a high degree of confidence.

However, despite these encouraging outcomes, the system encounters challenges related to environmental variability, dataset constraints, and computational requirements. These challenges present opportunities for further improvement and optimization. Future developments could involve the integration of a larger and more varied dataset, enhancing generalization across a wider array of species and imaging conditions. Moreover, the inclusion of bird audio data could support multimodal classification, providing more reliable identification even when visual data is limited or unclear.

To enhance accessibility and scalability, a mobile application could be created, allowing for offline or edge-based classification for users in remote or field environments. Additionally, the introduction of real-time video detection capabilities could enable ongoing tracking and identification of birds in natural settings. Furthermore, connecting with cloud-based platforms could facilitate seamless data storage and synchronization, thereby bolstering research and ecological monitoring initiatives.

The proposed system for bird classification and identification effectively illustrates the application of deep learning, specifically EfficientNet-B3, in automating the intricate process of identifying bird species from images. This system integrates comprehensive image preprocessing, sophisticated feature extraction, and transfer learning methodologies to achieve a classification accuracy exceeding 90% across a dataset comprising over 325 bird species. In contrast to conventional models that necessitate extensive training from the ground up, the incorporation of pre-trained weights and fine-tuning on bird-specific datasets facilitates a more efficient learning process with diminished computational expenses. Furthermore, the system's implementation as a web-based application enhances its accessibility for a diverse audience, including researchers, bird enthusiasts, and educators.

conservationists. The integration of post-processing steps such as confidence thresholding, label mapping, and informative result presentation further enhances the system’s usability and reliability. It represents an effective blend of scientific precision and practical application.

IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588
International Advanced Research Journal in Science, Engineering and Technology
Impact Factor 8.066 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 12, Issue 5, May 2025
DOI: 10.17148/IARJSET.2025.12579

REFERENCES

[1]. Penchala Abhinav, Sunitha Dhaval," Bird Species Bracket and vaticination Using Machine Learning Algorithms" 2024 IEEE Pune Section International Conference PuneCon).
[2]. Deepadarsini K T, Abhinithi M, Ashok A, Dr.Nandalal V "Bird Species Discovery using Deep literacy styles" 2023 International Conference on Research Methodologies in Knowledge Management.
[3]. Persia Abishal B, Sujitha Juliet." Image- Grounded raspberry Species Identification Using Machine literacy." 2023 9th International Conference on Advanced Computing and Communication Systems (ICACCS).
[4]. Mahsa Mohaghegh, Khaula Alizai, Minh Hoang, Kapil Patel, June Lee," Machine literacy for Conservation assessing Deep literacy and point birth in Bird Species Bracket in New Zealand", 2023 IEEE Asia Pacific Conference on Computer Science and Data Engineering CSDE).
[5]. B. Thamizhkani, S. Shalini, S. Jeyanthi, R. Aishwarya, Dr S. Senthil Kumar, R. Anitha," Scripting the Skies Beyond the Horizon with Machine Learning in Drone Shaped Bird Recognition", 2024 International Conference on Power, Energy, Control and Transmission Systems(ICPECTS).
[6]. Hari Kishan Kondaveeti, Kottakota Sai Sanjay, Karnam Shyam, Rayachoti Aniruth, Simhadri Chinna Gopi, Samparthi V S Kumar." Transfer literacy for Bird Species Identification" 2023 International Conference on Computational Systems and Communication (ICCSC)
[7]. Jie Xie, Mingying Zhu." aural Bracket of Bird Species Using an Early Fusion of Deep Features" catcalls 2023,
[8]. Shivam Mishra, Rumpa Ghatak, Vishal Kumar Singh, Shivam Kumar Singh, Anisha Mahato." raspberry Call Recognition using Acoustic- grounded Feature Selection Approach in Machine Learning." 2023 7th International Conference On Computing, Communication, Control And robotization (ICCUBEA).
[9]. Hanlin Wang, Yingfan Xu, Yan Yu, Yucheng Lin, Jianghong Ran." An Effective Model for a Vast Number of Bird Species Identification Grounded on aural Features." creatures 2022, 12.
[10]. Hanlin Wang, Yingfan Xu, Yan Yu, Yucheng Lin, Jianghong Ran." An Effective Model for a Vast Number of Bird Species Identification Grounded on aural Features." creatures 2022, 12.
[11]. Maysaa H. Abdulameer, Huda W. Ahmed, Israa S. Ahmed." raspberry Image Dataset Bracket using Deep Convolutional Neural Network Algorithm." International Conference on Data Science and Intelligent Computing ICDSIC 2022), Kerbala University, Iraq.
[12]. Wiam Rabhi, Fatima Eljaimi, Walid Amara, Zakaria Charouh, Amal Ezzouhri, Houssam Benaboud, Moudathirou Ben Saindou, Fatima Ouardi." An Integrated Framework for Bird Recognition Using Dynamic Machine literacy- Grounded Bracket." 2023 IEEE Symposium on Computers and Dispatches(ISCC).
[13]. Saritha N, Shruthi" An Automated Bird Species Bracket Using Deep literacy." 2024 Alternate transnational Conference on Advances in Information Technology (ICAIT- 2024).
[14]. Murugiaya Ramashini, Pg Emeroylariffion Abas, Liyanage C De Silva, Ulmar Grafe." Bird Sounds Bracket Using Linear Discriminant Analysis." 4th transnational Conference and Workshops on Recent Advances and inventions in Engineering (RAIE), IEEE 2019.
[15]. Persia Abishal B, Sujitha Juliet." Image- Grounded Bird Species Identification Using Machine literacy." 2023 9th transnational Conference on Advanced Computing and Communication Systems(ICACCS).