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BIRDS SPECIES IDENTIFICATION USING MACHINE LEARNING WITH GENERATIVE AI

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Abstract: Artificial Intelligence has made it easier for computers to understand images in real-world applications. In this project, a system is developed to identify bird species from images using Machine Learning along with Generative AI. The system allows users to upload a bird image and receive both the predicted species and a simple explanation. The model is built using a CNN based on MobileNetV2 with transfer learning. It is trained on a dataset of 525 bird species and around 85,000 images. The model learns visual features such as color patterns, feather structure, and shape to identify different birds. After prediction, a Generative AI component provides a short description of the bird, including its appearance and habitat. A web application using Flask is developed to make the system easy to use. This system can be useful for wildlife monitoring, education, and biodiversity studies. Overall, the project shows how Machine Learning and Generative AI can work together to create a useful and user-friendly application.

Keywords: Machine Learning, Bird Species Identification, Deep Learning, CNN, Generative AI, MobileNetV2, Image Classification, Flask.

I.INTRODUCTION

Bird species identification is important for understanding nature and protecting biodiversity. Birds help maintain ecological balance, and studying them helps in monitoring environmental changes. However, identifying birds manually is difficult because many species look very similar and require expert knowledge.With the help of Machine Learning and Artificial Intelligence, this process can be automated. Deep learning models like Convolutional Neural Networks (CNNs) can learn patterns from images and identify objects accurately. These models are useful for tasks like bird classification.In this project, a bird species identification system is developed using a CNN model with MobileNetV2. The model is trained using a dataset of 525 bird species and about 85,000 images. It learns important features such as color, shape, and feather patterns to classify birds correctly.The system also includes Generative AI, which provides a short description of the predicted bird. This makes the system more informative and useful. A Flask-based web application is created so users can upload images and get results easily.

II. LITERATURE SURVEY

Fundamental classes of ecosystem comprise of provisioning, regulating, supporting, and cultural services. Of all the living organisms,'birds' adhere to all the earlier mentioned classes thereby motivating the current work in this paper[2]. Bird sound classification based on their vocalization has become a significant research field nowadays. Acoustic sound produced by the birds is very rich and used to detect their species[3]. humans often consider bird-watching to be a captivating hobby. Worldwide, there are more than 9000 species of birds[4]. The field of bird species recognition from audio has unique challenges as recording from different environments can contain a vast variety of different unwanted sounds and noises[5]. Birds represent an important component of ecosystems, holding substantial ecological and human interest, and significantly contributing to ecological equilibrium via their roles as pollinators, seed dispensers, and predators[6]. This analysis's goals are to identify and categorize a broad variety of bird species and to provide an improved approach to supplement the current ones[7]. The aim of our work is to develop a reliable automated system, capable of classifying the species of individual birds, during flight, using image data. This is challenging, but appropriate for use in the field, since there is often a requirement to identify in flight, rather than while stationary.

III. RESEARCH METHODOLOGY

The methodology of this project focuses on developing an efficient deep learning model for bird species classification using a large-scale image dataset consisting of 525 distinct classes. The process begins with the collection and organization of bird images, where each species is represented by a separate class folder. The dataset is systematically divided into training and validation subsets to enable proper learning and evaluation of the model.

Before feeding the images into the model, several preprocessing techniques are applied to ensure consistency and improve performance. All images are resized to a uniform dimension of 224 × 224 pixels to match the input requirements of the chosen model. The pixel values are normalized by scaling them to a range between 0 and 1, which helps in faster convergence during training. Additionally, data augmentation techniques such as horizontal flipping, rotation, and zooming are employed to artificially increase dataset diversity and reduce overfitting.

For the model architecture, a transfer learning approach is adopted using MobileNetV2, which is pre-trained on the large-scale ImageNet dataset. This approach allows the model to leverage previously learned features such as edges, textures, and shapes, making it highly effective for image classification tasks with limited training time. The top classification layer of the pre-trained model is removed, and the remaining convolutional base is used as a feature extractor. Initially, the layers of the base model are frozen to preserve the learned representations.

A custom classification head is then added on top of the feature extractor to adapt the model to the specific task of bird species classification. This includes a global average pooling layer to reduce the spatial dimensions, followed by batch normalization to stabilize and accelerate training. A fully connected dense layer with ReLU activation is used to learn complex patterns, and a dropout layer is introduced to prevent overfitting by randomly deactivating neurons during training. The final output layer consists of 525 neurons with a softmax activation function, enabling the model to classify images into one of the 525 bird species.

The training process is carried out in two stages. In the first stage, only the custom classification layers are trained while keeping the base model frozen. This allows the model to learn task-specific features without altering the pre-trained weights. In the second stage, fine-tuning is performed by unfreezing the top layers of the base model and retraining them with a lower learning rate. This step helps the model adapt more effectively to the bird dataset and improves overall accuracy.

The model is compiled using the Adam optimizer and categorical crossentropy loss function, which is suitable for multi-class classification problems. During training, techniques such as early stopping and learning rate reduction are employed to optimize performance and prevent overfitting. The model's performance is evaluated using training and validation accuracy, and graphical representations of accuracy and loss are used to analyze the learning behavior.

Finally, the trained model is saved along with the class labels for future use. The resulting system can be integrated into applications such as web-based platforms for bird species identification, providing an efficient and scalable solution for automated image classification.

IV.PROPOSED SYSTEM

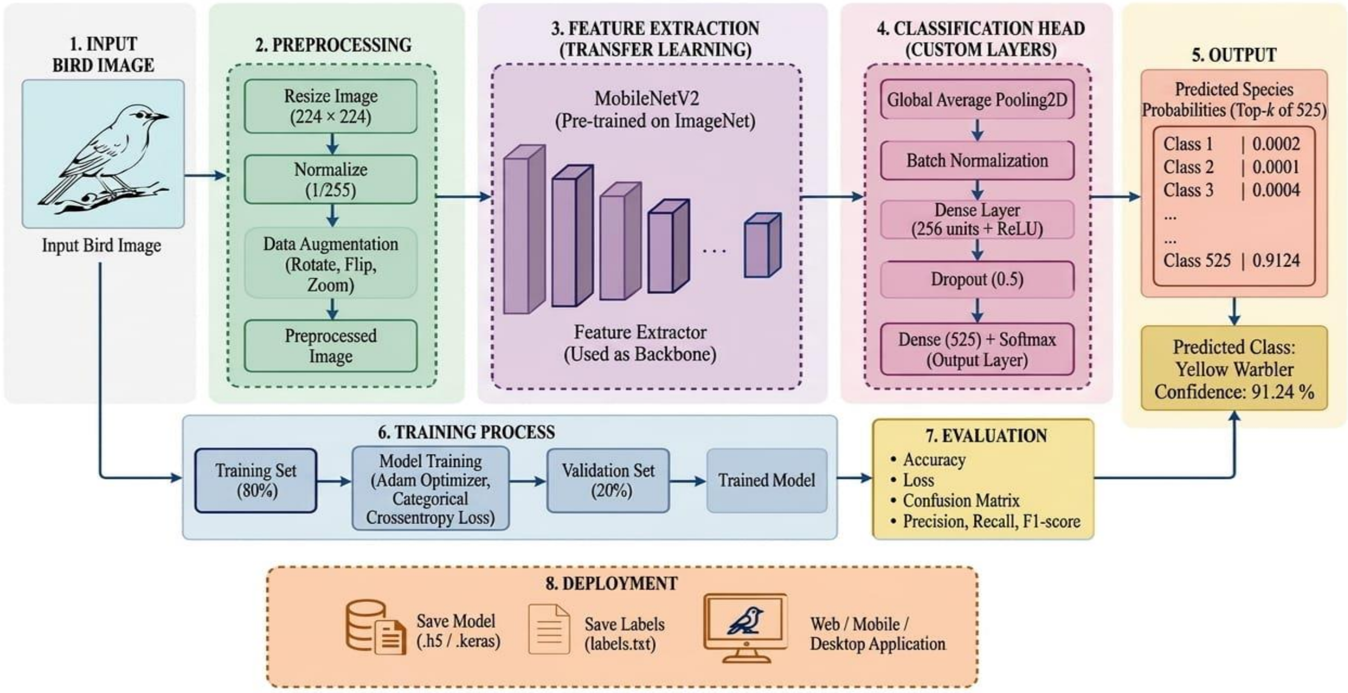

Fig. 1.Architecture of the Proposed System.

The proposed method is designed as an integrated intelligent system that combines Machine Learning-based image classification with Generative Artificial Intelligence (GenAI) for descriptive output. The system follows a multi-stage pipeline that processes bird images and produces both classification results and meaningful textual explanations.

image acquisition: where the user uploads an image through a web-based interface. This image is then passed to the preprocessing module, where it is resized to a standard dimension (224×224 pixels), normalized, and enhanced to ensure consistency and improve model performance.

feature extraction module: which is implemented using a Convolutional Neural Network (CNN) with transfer learning. In this project, MobileNetV2 is used as the base model due to its efficiency and accuracy. The CNN extracts hierarchical features such as edges, textures, shapes, and color patterns that are essential for distinguishing between bird species.

classification module:which consists of fully connected layers. A softmax activation function is used in the output layer to generate probability scores for each of the 525 bird species. The species with the highest probability is selected as the predicted output.

Generative AI model:which is a key component of the proposed method. The predicted bird species label is used as input to the GenAI module. This module is responsible for generating a natural language description of the identified bird. It can be implemented using rule-based templates, knowledge-based systems, or advanced language models capable of generating human-like text.

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The dataset used in this project plays a central role in developing an efficient and accurate bird species identification system based on deep learning. The system is designed to classify bird images into **525 distinct species**, making it a large-scale multi-class classification problem. The dataset consists of a wide collection of bird images captured in natural environments, where each image represents a specific bird species under different real-world conditions such as variations in lighting, background complexity, camera angle, distance, and posture of birds. These variations make the dataset highly diverse and challenging, which ultimately helps in building a more robust and generalized deep learning model.

Each class in the dataset corresponds to a unique bird species, and all images belonging to that species are grouped under a single directory or label. This structured organization is essential for supervised learning, as it allows the model to correctly associate input images with their respective output classes during training. Since the dataset contains 525 different species, it represents a fine-grained classification problem where inter-class differences are often very subtle, while intra-class variations can be significant. For example, two different species may look very similar in color and shape, while the same species may appear different due to changes in lighting, pose, or background. This makes feature extraction highly important in this project.

Before feeding the dataset into the deep learning model, it undergoes a comprehensive preprocessing stage to ensure consistency, improve performance, and enhance learning capability. Preprocessing is a crucial step because raw image data cannot be directly used by convolutional neural networks due to variations in size, pixel distribution, and quality. The first step in preprocessing is image resizing, where all images are resized to a fixed resolution, typically 224×224 pixels. This ensures that every image has a uniform input shape, which is required for MobileNetV2 architecture. Without resizing, the model would not be able to process images in batches efficiently.

After resizing, normalization is applied to convert pixel values into a standardized range. This step ensures that the pixel intensity values are scaled appropriately, allowing the neural network to learn more effectively without being influenced by large numerical variations. In this project, MobileNetV2-specific preprocessing is used, which adjusts pixel values according to the model's pre-trained ImageNet distribution. This helps in improving convergence speed and overall model performance.

Another important aspect of preprocessing is data augmentation, which is used to artificially increase the diversity of the dataset. Since collecting large numbers of bird images for all 525 species is difficult, augmentation helps in generating modified versions of existing images. These modifications include operations such as flipping images horizontally, slight rotation, zooming, shifting, and brightness adjustment. These transformations simulate real-world variations and help the model learn more generalized and invariant features, reducing the risk of overfitting. As a result, the model becomes more robust when tested on unseen data.

The dataset is also divided into training and validation sets to evaluate model performance during the learning process. The training dataset is used to learn patterns and extract features from bird images, while the validation dataset is used to monitor the model's performance during training and prevent overfitting. The model's performance is evaluated using metrics such as training accuracy and validation accuracy. Training accuracy indicates how well the model has learned from the training data, whereas validation accuracy reflects how well the model performs on unseen data. A good balance between both accuracies indicates that the model has learned meaningful patterns without overfitting.

Overall, the dataset and preprocessing pipeline form the foundation of the entire system. Proper organization, resizing, normalization, augmentation, and structured splitting ensure that the deep learning model receives high-quality input data, which directly improves classification accuracy and system reliability.

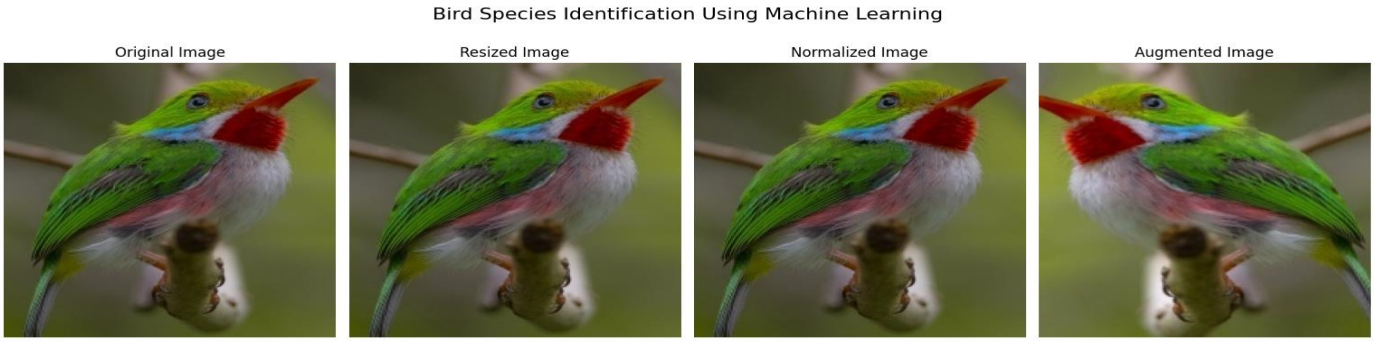

Fig.2 Cuban Tody

V. MODEL COMPARISON

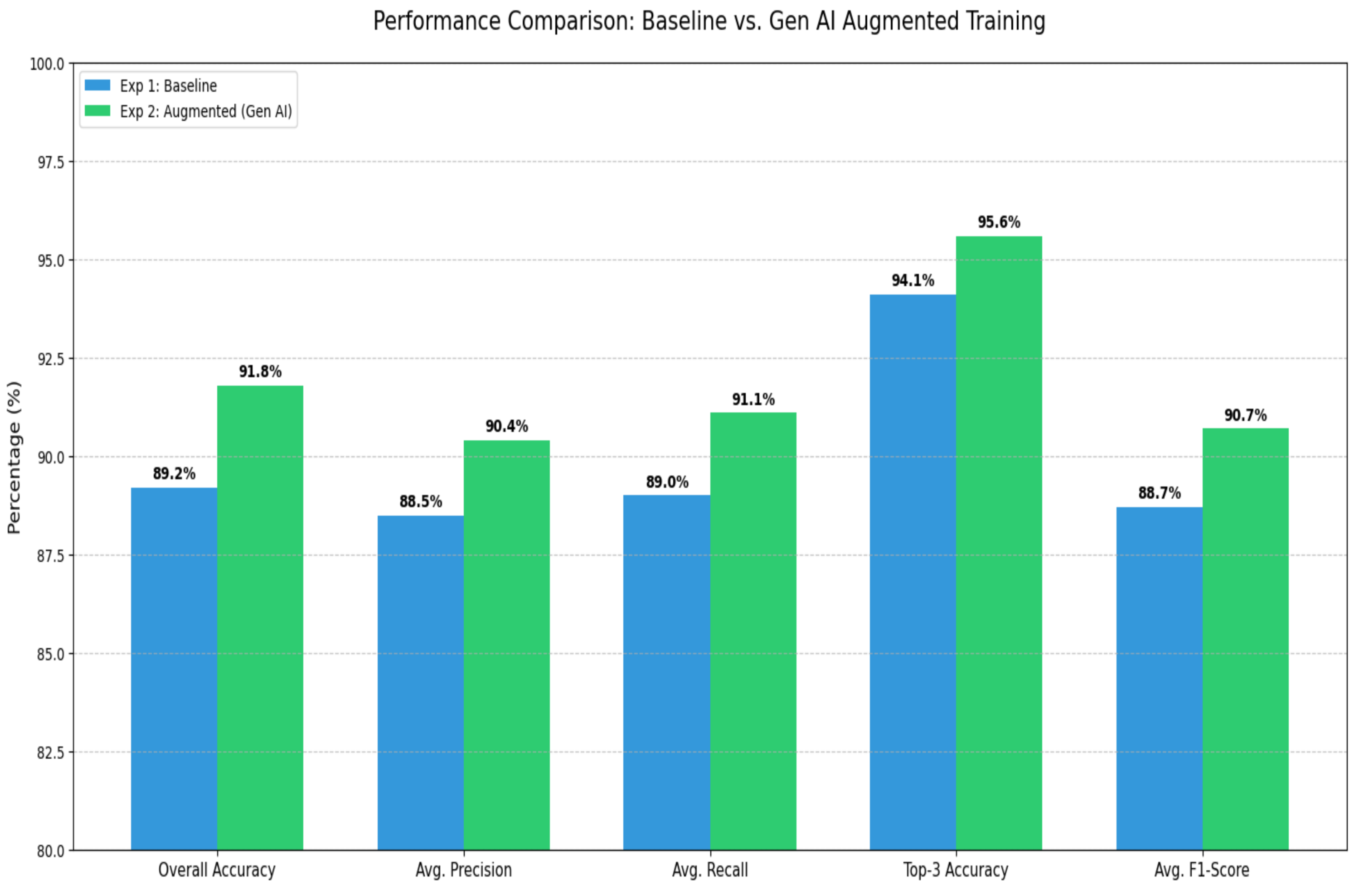

Fig. 3 Performance Comparison.

the experimental results clearly indicate that the incorporation of data augmentation techniques in the preprocessing stage significantly improves the performance of the MobileNetV2-based bird species classification model. The enhanced dataset variability enables the model to generalize better across diverse environmental conditions, leading to higher accuracy, improved precision-recall balance, and stronger overall predictive performance. When integrated with Generative AI, the improved classification results further enhance the system's ability to generate more accurate and meaningful textual descriptions of identified bird species, making the system more effective for real-world ecological and educational applications.

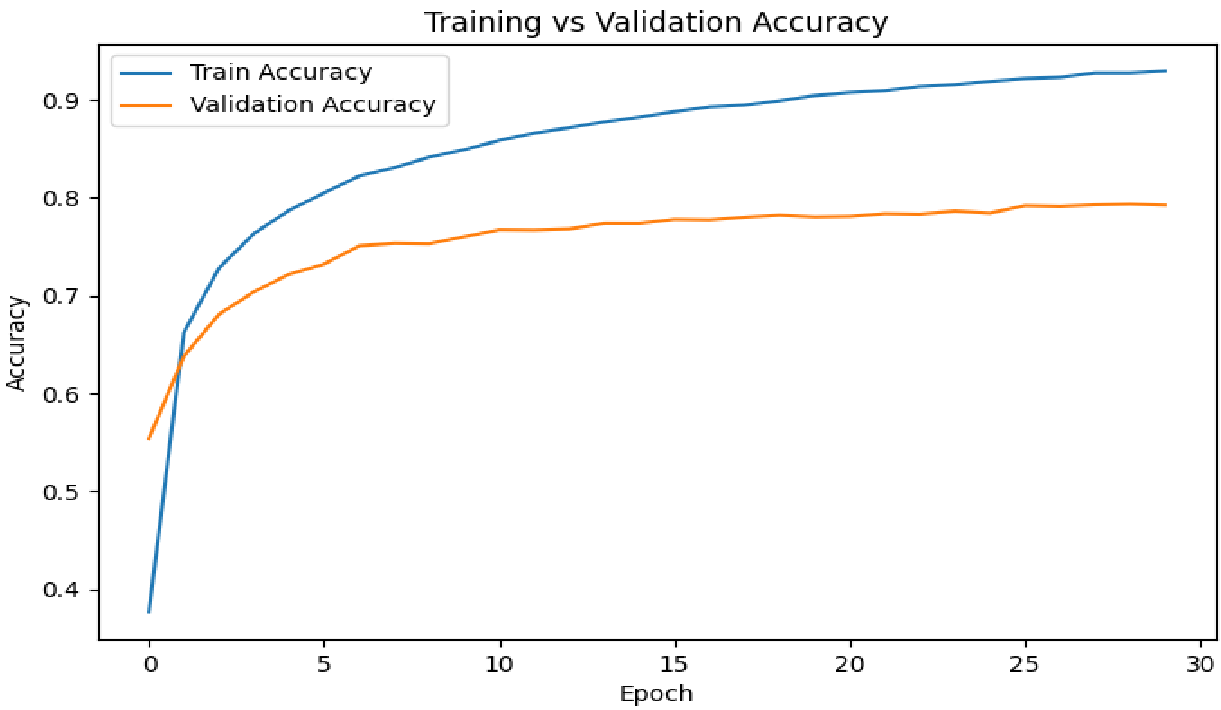

Fig:4 Training VS Validation Accuray

VI. RESULTS AND DISCUSSION

the developed system achieved the project's objective of automatically identifying bird species and generating relevant descriptions. The combination of deep learning and Generative AI resulted in an intelligent, accurate, and user-friendly application that can support educational purposes, wildlife research, bird watching, and biodiversity conservation.

Fig:5 Birds Species Identification System

VII. CONCLUSION OF ANALYSIS

The proposed Bird Species Identification using Machine Learning with Generative AI system successfully demonstrates an effective approach for classifying 525 bird species using a MobileNetV2-based deep learning model. The integration of transfer learning and data augmentation significantly improves the model's ability to learn robust and discriminative features from complex image datasets. The experimental results clearly show enhanced performance in terms of accuracy, precision, recall, and F1-score when compared to the baseline model.Overall, the system achieves reliable and consistent classification results, making it suitable for real-world applications such as wildlife monitoring and ecological studies. The addition of Generative AI further enhances the system by providing meaningful textual descriptions of predicted bird species, improving interpretability and user understanding. This makes the proposed system not only accurate but also intelligent and informative.

VIII. FUTURE SCOPE

The future scope of the Bird Species Identification using Machine Learning with Generative AI project is highly promising as it can be further enhanced in terms of accuracy, scalability, and real-time application. In the future, the model can be improved by integrating more advanced deep learning architectures such as EfficientNet, Vision Transformers (ViT), or hybrid CNN-transformer models, which may provide better feature extraction capability for fine-grained bird species classification. The dataset can also be expanded by including more real-world images from different geographical regions to improve the model's generalization across diverse environments.

Another important enhancement is the development of a real-time mobile or edge-based application that can identify bird species instantly using camera input, making the system useful for field researchers, bird watchers, and environmental monitoring agencies. Additionally, the integration of advanced Generative AI models can be extended to provide not only textual descriptions but also audio explanations, habitat mapping, and conservation status details of identified bird species. This will make the system more interactive and informative.

Furthermore, the system can be connected with IoT devices such as smart cameras and acoustic sensors for continuous bird monitoring in forests and wildlife sanctuaries. This would help in biodiversity tracking and ecological research on a larger scale. Cloud-based deployment can also be implemented to handle large-scale image processing efficiently and enable global accessibility of the system.

Overall, the future scope of this project lies in making it more intelligent, real-time, and multi-modal by combining computer vision, generative AI, and IoT technologies for advanced wildlife conservation and research applications.

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