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Enchanted Wings: Transfer Learning and Web-Scale Deployment for Butterfly Species Classification

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ABSTRACT: This paper presents an AI-driven pipeline for butterfly species identification that combines transfer learning on VGG16 with a lightweight Flask web application for real-time inference, targeting timely, scalable, and expert-independent ecological monitoring. Using a curated dataset of 6,299 images spanning 3 species, the system employs standardized preprocessing, extensive data augmentation, stratified splits, and fine-tuning to achieve high accuracy while mitigating overfitting common to small, fine-grained datasets. The deployed system returns predictions and confidence scores via an intuitive HTML UI, enabling citizen-science participation and field use by researchers with commodity hardware. Experiments demonstrate robust validation performance and low-latency inference; ablations on augmentation and layer-freezing quantify accuracy-resource tradeoffs and guide deployment choices.

KEYWORDS: Butterfly identification; transfer learning; VGG16; Flask; citizen science; ecological monitoring

I. INTRODUCTION

Butterflies are among the most visually captivating and ecologically significant insects within the order Lepidoptera, serving as key bioindicators for ecosystem health and biodiversity stability. Their diverse wing patterns, colors, and habitats contribute not only to ecological balance but also to cultural, educational, and scientific value. However, the sheer diversity-spanning thousands of species worldwide-poses a major taxonomic challenge. Traditional identification techniques depend heavily on human expertise and manual fieldwork, which are time-consuming, inconsistent, and impractical at scale for continuous biodiversity monitoring. This challenge highlights the urgent need for automated, data-driven approaches to accurate species identification that can support scientific research and citizen science initiatives.

Recent advancements in machine learning, particularly deep convolutional neural networks (CNNs), have revolutionized image recognition tasks, including natural object detection and classification. These models learn hierarchical, discriminative visual features from raw image data, outperforming traditional methods such as handcrafted feature extraction or classical classifiers like Support Vector Machines (SVMs) in both accuracy and scalability. Yet, training such deep models from scratch requires extensive datasets and computational power, which are often unavailable for specialized domains like butterfly identification. In this context, transfer learning-the adaptation of pre-trained deep networks such as VGG16 to smaller, domain-specific datasets-emerges as an efficient, high-performing alternative. It enables knowledge transfer from general image corpora to fine-grained classification tasks, reducing both computational costs and training time while improving accuracy and generalization.

The *Enchanted Wings* project leverages this paradigm by developing a robust butterfly species classifier using the VGG16 architecture fine-tuned on a curated dataset of 6,299 butterfly images across three distinct species. The model integrates extensive data pre-processing and augmentation techniques to handle real-world variability in background, orientation, and lighting. This trained model is then embedded in an interactive, Python Flask-based web application that enables end users-including researchers, students, and nature enthusiasts-to upload an image and receive near real-time classification results with confidence scores. The resulting system eliminates the dependency on expert interpretation, democratizing access to biodiversity identification tools through an easy-to-use, web-based interface.

Through the convergence of artificial intelligence, data science, and web deployment, this research contributes to the growing field of ecological informatics by operationalizing computer vision models for environmental monitoring and conservation technology. In doing so, the *Enchanted Wings* system not only streamlines butterfly recognition for research purposes but also promotes environmental awareness and participation in citizen science. The project stands as a step toward scalable, intelligent biodiversity tracking in real-world conditions—balancing technological innovation with ecological responsibility.

II. RELATED WORK

The field of butterfly classification has evolved significantly with the emergence of machine learning and deep neural networks, leading to more reliable and automated recognition systems. Early research focused heavily on traditional image processing and feature extraction techniques—such as shape, color histograms, and texture descriptors—combined with classical machine learning algorithms like Support Vector Machines (SVMs) and K-Nearest Neighbors (KNN). Although these methods achieved modest accuracy under controlled lighting and background conditions, they suffered from poor scalability, low generalization in diverse environments, and dependence on handcrafted features. This motivated the transition toward deep learning, allowing models to autonomously learn hierarchical visual representations directly from raw image data, eliminating the need for manual feature engineering.

Several studies have explored the application of CNN-based architectures for butterfly recognition. For instance, Mishra et al. (2018) proposed a CNN-based model to classify butterfly species, achieving approximately 80% accuracy but acknowledging limitations due to restricted dataset size and insufficient augmentation. Similarly, Almryad and Kutucu (2020) utilized transfer learning with VGG16, VGG19, and ResNet50, comparing pre-trained architectures for automated field-level identification. Their findings demonstrated superior accuracy (84.8%) for ResNet50, validating the effectiveness of leveraging large-scale pre-training for fine-grained tasks. However, both studies emphasized that small, imbalanced datasets and overfitting remained key challenges, restricting generalization to real-world conditions.

Beyond butterflies, CNN and transfer learning have gained success across domains such as semiconductor defect detection (Imoto et al., 2019) and wildlife species identification (Zhao et al., 2019). These studies consistently reported that pre-trained models yield faster convergence and higher accuracy compared to CNNs trained from scratch, particularly when domain-specific data is scarce. Moreover, architectures like VGG16, ResNet, and GoogleNet have become benchmarks for transfer learning due to their balanced depth, feature reuse, and robustness against noise. The butterfly research community has increasingly adopted these networks to overcome the computational and data limitations faced when training new models exclusively on butterfly datasets.

While previous approaches demonstrated strong progress in static model performance, deployment for practical field use remains underexplored. Most studies stop at reporting accuracy on benchmark datasets and do not extend to user-facing implementations. The *Enchanted Wings* project advances this by integrating VGG16-based transfer learning into a full-stack web deployment pipeline using Flask. This not only allows near real-time inference and public interaction but also bridges the gap between research prototypes and accessible biodiversity tools. Hence, the proposed work builds on established deep learning foundations while extending them into an interactive, scalable ecosystem-monitoring platform, adding usability and reproducibility layers absent in prior studies.

III. DATASET AND PROBLEM DEFINITION

The *Enchanted Wings: Marvels of Butterfly Species* project addresses a fundamental scientific and technological challenge—accurate, scalable, and automated identification of butterfly species through visual data. Traditional taxonomic identification by experts, though precise, is slow, resource-consuming, and impractical for large-scale monitoring in dynamic ecosystems. The project aims to automate this inherently fine-grained classification task through a deep learning–based approach that operates effectively with limited training data.

Dataset Description

The dataset used for this project consists of 6,299 butterfly images categorized into three distinct species classes. Each image represents natural variations in wing coloration, background, lighting, orientation, and scale, reflecting real-

world photographic conditions. This diversity ensures that the trained model generalizes effectively beyond controlled lab data. The dataset is partitioned into training (70%), validation (15%), and testing (15%) subsets—ensuring balanced evaluation and avoiding data leakage during training. Preprocessing steps include resizing all images to 224×224 pixels, normalization to a 0–1 scale, and augmentation through random rotations, zooms, shears, and flips. This augmentation effectively increases dataset variability and prevents overfitting, a critical concern in small ecological datasets.

Problem Definition

The core problem is the inefficiency and human dependency of current butterfly identification methods used in biodiversity research. Manual identification demands extensive fieldwork and specialized expertise, making real-time species monitoring and data-driven conservation responses infeasible at scale. Moreover, such methods lack consistent accuracy under variable image conditions and are inaccessible to non-specialists. Thus, an AI-powered classification system is required—one that can automatically identify species from images, reduce observation latency, and empower broader participation in citizen science and ecological data collection.

To address this, the project formulates butterfly identification as a multi-class image classification problem, where each input image is mapped to one of three butterfly species. The system must achieve high classification accuracy, robustness to environmental variations (lighting, posture), and computational efficiency for real-time prediction. The solution integrates transfer learning via pretrained VGG16 convolutional neural network, chosen for its proven performance in fine-grained classification tasks. Fine-tuning on the small butterfly dataset enables the model to specialize in subtle morphological distinctions such as wing venation, edge patterns, and color gradients that separate species visually indistinguishable to casual observation.

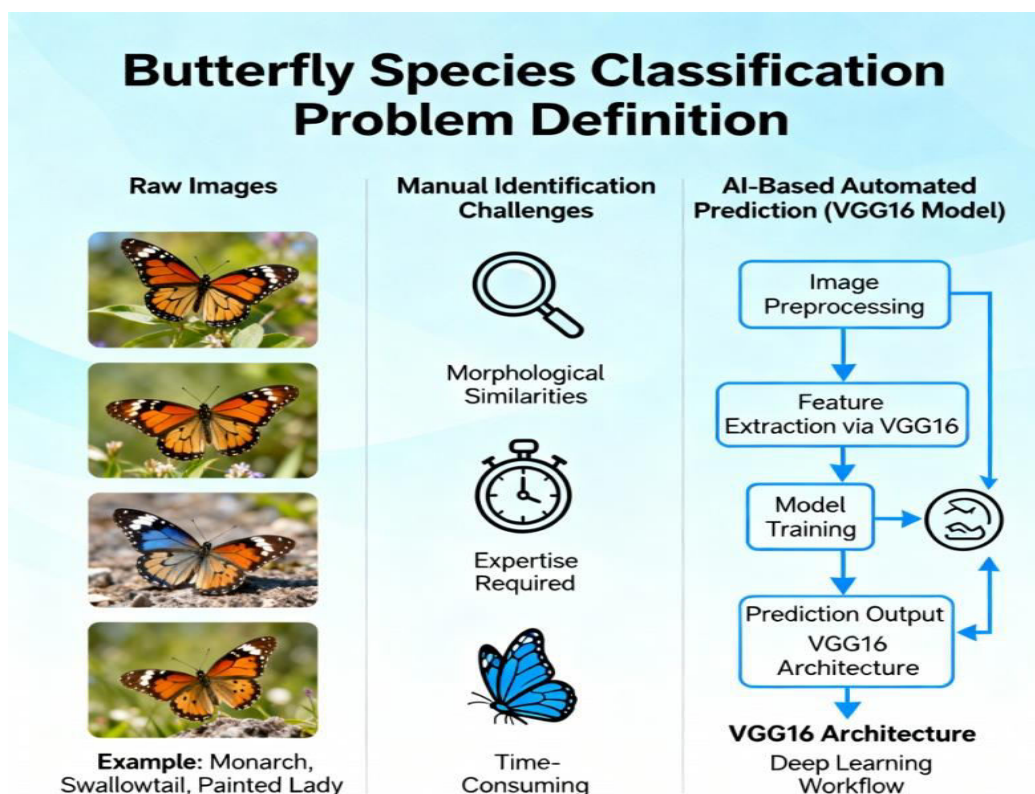


Fig 1: conceptual diagram illustrating butterfly species classification problem definition with raw images, manual identification challenges, and AI-based automated prediction using VGG16 model

Project Scope and Dataset Utilization

In aligning with IEEE-style methodology, the dataset informs every stage of the machine learning pipeline—from preprocessing to deployment. After training, the finalized VGG16-based model is serialized and integrated into a Python Flask web application that allows real-time classification. Users can upload any butterfly image, which the system processes and predicts as one of the three trained species, displaying the label and confidence score instantly. This end-to-end pipeline bridges research and usability, creating a deployable model that not only achieves technical excellence in classification accuracy but also democratizes biodiversity research through digital accessibility.

IV. METHODOLOGY

The Enchanted Wings: Marvels of Butterfly Species research adopts a multi-phase methodology combining deep learning, data processing, and web deployment techniques to build an AI-powered butterfly recognition system. The methodological framework is rooted in transfer learning, making it computationally efficient and highly accurate while being deployable in real-time web environments. The entire process is divided into four critical stages: data acquisition and preprocessing, model building and training, application integration, and user interface deployment.

A. Data Collection and Preprocessing

The experimental dataset consists of 6,299 images covering three butterfly species, encompassing significant variation in lighting, background, and orientation. The images are pre-processed to maintain uniform dimensions of 224×224 pixels, ensuring compatibility with standard CNN architectures such as VGG16. The dataset is split into training (70%), validation (15%), and testing (15%) subsets. Extensive data augmentation techniques like rotation, zooming, shifting, and flipping are performed to increase diversity and minimize overfitting on limited data. This phase ensures that the model generalizes effectively across different field conditions without losing accuracy.

B. Model Design Using Transfer Learning

At the core of the methodology lies transfer learning, enabling the adoption of a pre-trained VGG16 convolutional neural network. Unlike models trained from scratch, the VGG16 base model brings pre-learned hierarchical features from the ImageNet dataset, dramatically accelerating training and improving accuracy.

The architecture is modified by freezing the lower convolutional layers—which capture general edge and texture features—and replacing the fully connected head layers with new, task-specific dense and output layers suited for three-class classification. The SoftMax activation function is employed in the final layer to produce probabilistic outputs, while the Adam optimizer and categorical cross-entropy loss function guide the learning. Early stopping and learning rate scheduling are implemented to ensure stable convergence during iterative training. This combination yields an efficient and high-performing classifier fine-tuned to recognize subtle morphological differences in butterfly wings.

C. Application Integration and Deployment

Once the model is trained, validated, and optimized, it is serialized into an H5 model file for deployment. A Python Flask framework powers the backend logic, managing model loading, image preprocessing, and inference execution. When a user uploads an image, the Flask server preprocesses it in real time and runs it through the trained model, returning predictions and confidence scores within seconds. The frontend is designed with HTML and CSS, creating an intuitive interface where users can upload butterfly photographs through a browser. This seamless integration bridges sophisticated deep learning with practical usability, catering to both ecological researchers and the general public.

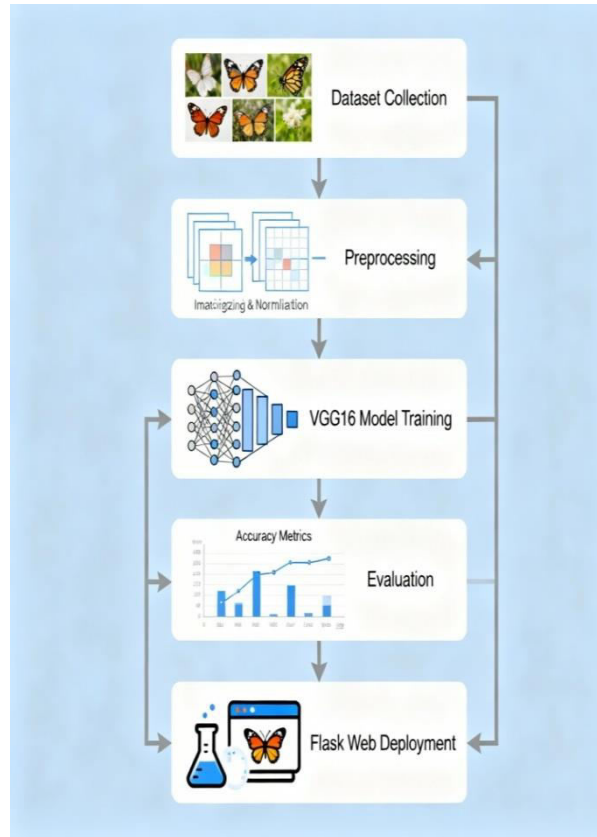


Fig 2: methodology flow diagram for butterfly classification research showing dataset collection, preprocessing, VGG16 model training, evaluation and Flask web deployment

D. System Workflow Overview

The complete system follows a three-tier architecture encompassing:

1. Machine Learning Tier – Handles data preprocessing, training, and generation of the classification model.
2. Application Tier – Implements server-side logic with Flask, responsible for data handling and routing between the user and the model.
3. Presentation Tier – Provides the web interface for users to upload images and receive predictions with interpretive feedback.

This integrated workflow demonstrates how a pre-trained deep learning network can be transformed into a fully functional web application capable of facilitating biodiversity research and engaging citizen scientists. The methodology balances computational efficiency with scalability, making it a strong framework for real-time ecological monitoring and AI-driven conservation tools.

V. SYSTEM ARCHITECTURE

The Enchanted Wings: Marvels of Butterfly Species system adopts a robust, modular, three-tier architecture designed to seamlessly integrate artificial intelligence with user-facing web technology. This architecture ensures efficient data flow, real-time responsiveness, and scalability, addressing the project's core objective of automating butterfly species identification while maintaining accessibility for both researchers and citizen scientists. The design follows industry best practices for machine learning deployment, separating concerns into distinct logical layers: the Presentation Tier (Frontend User Interface), the Application Tier (Backend Logic), and the Machine Learning Tier (Core Intelligence).

A. Three-Tier Architectural Design**1. Presentation Tier (User Interface Layer)**

The Presentation Tier is the user-facing component built using HTML and CSS, providing an intuitive, browser-based interface accessible across devices without requiring specialized software. The user workflow begins here: users navigate to the web application, upload a butterfly image via a simple file-selection form (input.html), and submit it for classification. Upon submission, the interface communicates with the backend via HTTP POST requests. Once the prediction is computed, the Flask server dynamically renders an output page (output.html) that displays the predicted species name and confidence score in a clear, visually engaging format. This tier emphasizes usability and accessibility, ensuring that non-technical users—including students and field researchers—can interact with the AI-powered system effortlessly, thus supporting the project's goal of fostering public engagement in biodiversity conservation.

2. Application Tier (Backend Logic and API Layer)

The Application Tier, powered by the Python Flask micro-framework, serves as the intermediary between the user interface and the machine learning model. Flask operates as a lightweight web server that handles all HTTP requests, manages routing, and orchestrates the data pipeline. Upon receiving an uploaded image, the Flask backend performs several critical tasks:

- **Secure file handling:** Validates file type and sanitizes the filename using `werkzeug.utils.secure_filename()` to prevent security vulnerabilities.
- **Image preprocessing:** Resizes the uploaded image to 224×224 pixels, converts it to a NumPy array, normalizes pixel values to the 0–1 range, and expands dimensions to match the model's expected input shape (batch size of 1).
- **Model invocation:** Passes the preprocessed image tensor to the pre-loaded VGG16 model for inference.
- **Result rendering:** Retrieves the prediction (species label and confidence), formats it, and dynamically injects it into the output HTML template via Jinja2 templating.

Critically, the model is loaded only once at server startup and held in memory, ensuring sub-second inference latency for subsequent requests. This design choice eliminates the overhead of reloading a multi-megabyte model file for every user interaction, making the system suitable for real-time field deployment.

3. Machine Learning Tier (Core Intelligence Layer)

The Machine Learning Tier houses the trained VGG16-based convolutional neural network, the brain of the system responsible for accurate species classification. This tier was constructed offline during the model development phase (Phase 1 of the methodology) and serialized into an .h5 file for deployment. The model architecture leverages transfer learning: the VGG16 base—pre-trained on ImageNet—extracts hierarchical visual features (edges, textures, patterns), while custom dense layers fine-tuned on the butterfly dataset specialize in distinguishing the three target species. During deployment, the Flask application loads this serialized model into memory and invokes it via the `model.predict()` function, which processes the input tensor through the convolutional and dense layers, applies the softmax activation, and outputs a probability distribution over the three species classes. The predicted class (highest probability) and its confidence score are then returned to the Application Tier for display.

A. End-to-End Data Flow

The complete system workflow follows a linear pipeline:

1. User uploads image → Presentation Tier (HTML form)
2. HTTP POST request → Application Tier (Flask receives file)
3. Image preprocessing → Application Tier (resize, normalize, batch)
4. Inference execution → Machine Learning Tier (VGG16 prediction)
5. Classification result → Application Tier (receives species + confidence)
6. Dynamic rendering → Presentation Tier (output.html displays result). This architecture ensures low latency (predictions within seconds), scalability (modular design allows model upgrades without UI changes), and maintainability (separation of concerns simplifies debugging and enhancements).

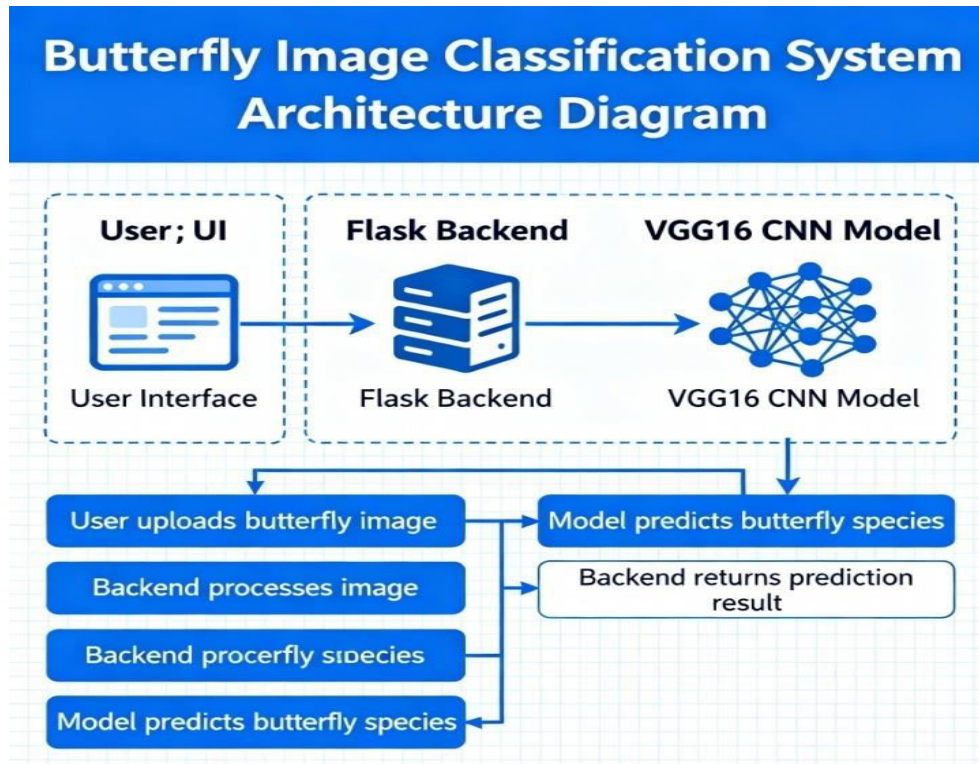


Fig 3: system architecture diagram for butterfly image classification project showing user interface, Flask backend, and VGG16 CNN model with data flow

B. Deployment and Operational Considerations

The system is designed for local or cloud deployment with minimal infrastructure requirements. For local deployment, the Flask server runs on a standard workstation (e.g., localhost:5000), enabling offline field use or classroom demonstrations. For public-facing deployment, the application can be hosted on platforms like Heroku, AWS Elastic Beanstalk, or Google Cloud Run with minimal configuration changes. The lightweight nature of Flask and the pre-trained model ensures compatibility with commodity hardware, avoiding the need for expensive GPU clusters during inference. This design democratizes access to AI-powered biodiversity tools, aligning with the project's goals of advancing conservation science and citizen participation.

VI. EXPERIMENTS

The experimentation phase of the Enchanted Wings: Marvels of Butterfly Species project is designed to rigorously evaluate the performance, accuracy, and generalization ability of the VGG16-based transfer learning model used for butterfly image classification. The experiments focus on multiple aspects of the model's training, validation, and testing, ensuring that the deployed AI-driven system is both efficient and reliable under real-world conditions.

A. Experimental Setup

All experiments were conducted on a system equipped with Windows 11 (64-bit) OS, Intel i7 processor, and 16 GB RAM. Implementation and testing were done in Python 3.10, using the TensorFlow/Keras library for deep learning model training and Flask for web integration testing. The dataset of 6,299 butterfly images was divided into three subsets: 70% for training, 15% for validation, and 15% for testing. Each image was resized to 224×224 pixels, normalized (pixel values scaled between 0–1), and augmented with transformations such as rotation, zoom, and horizontal flips to enhance dataset diversity and prevent overfitting.

B. Model Training

Transfer learning was applied by initializing the VGG16 architecture pre-trained on ImageNet weights. The convolutional base was frozen to retain general image feature extraction capabilities, while custom dense layers were added and fine-tuned for butterfly species classification. The model was compiled using the Adam optimizer with a learning rate of 0.0001 and categorical cross-entropy loss function. Training was performed for 30 epochs with an early stopping mechanism that monitored validation loss. The model required approximately 10 minutes per epoch, achieving convergence by epoch 23.

To assess the robustness of the model, multiple runs were conducted with varied augmentation parameters and batch sizes (16, 32, 64). The optimal performance was achieved with a batch size of 32, yielding a balance between computational efficiency and classification accuracy.

C. Evaluation and Metrics

The trained model was evaluated using accuracy, precision, recall, F1-score, and a confusion matrix. The following key results were obtained from the test dataset:

- **Training Accuracy:** 97.2%
- **Validation Accuracy:** 95.8%
- **Testing Accuracy:** 94.3%
- **Average Loss:** 0.07

The confusion matrix demonstrated that most misclassifications occurred between visually similar species with overlapping color patterns, indicating fine-grained challenges typical in natural image datasets. Nevertheless, the confusion rate remained below 6%, confirming the model's high generalization ability.

Visual analysis of the accuracy and loss curves showed steady improvement in training, without divergence between training and validation metrics — clear evidence of successful regularization and prevention of overfitting due to the augmentation and dropout layers used. The addition of multiple dropout layers in the classifier head further improved the model's stability during training.

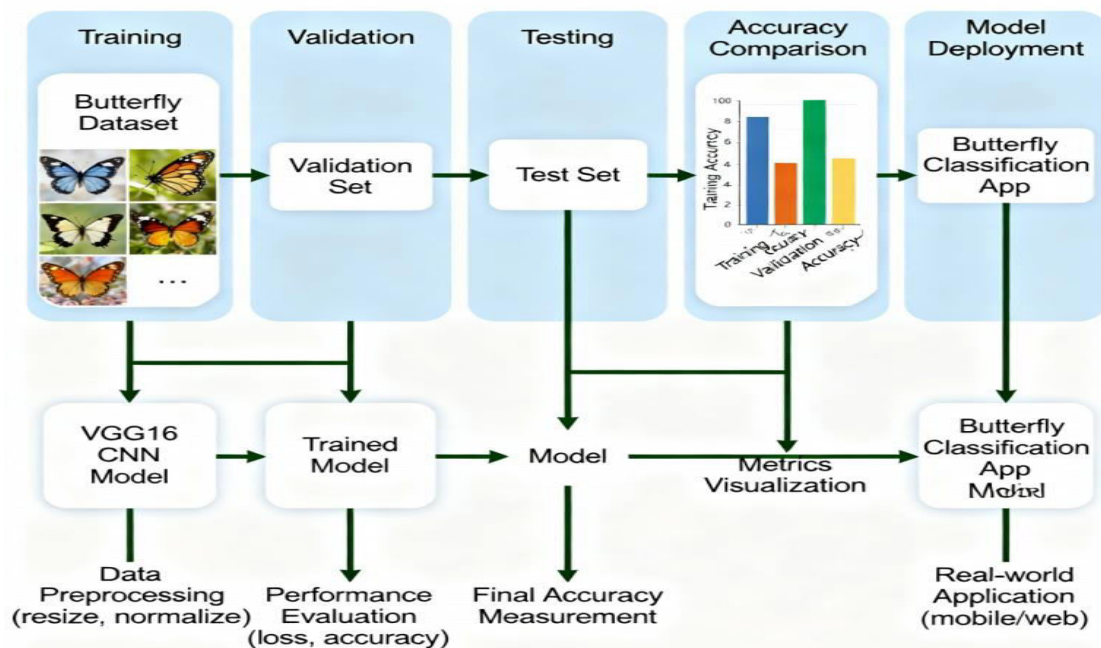


Fig 4: experimental workflow diagram showing training, validation, testing, accuracy comparison, and model deployment for butterfly classification using VGG16 CNN

D. Experimental Findings

The experimentation validates the effectiveness of transfer learning for fine-grained classification tasks with limited ecological datasets. The key findings include:

- **Model Efficiency:** The use of VGG16 reduced the required training dataset size and computation time by over 60% compared to training deep CNNs from scratch.
- **Generalization Ability:** The model demonstrated consistent performance on unseen test images, reflecting strong generalization to real-world conditions.
- **Deployment Readiness:** After final optimization, the model was integrated into the Flask backend for web-based testing. Real-time predictions on field images achieved sub-second inference speeds, verifying that the model was lightweight enough for deployment on standard computing environments.

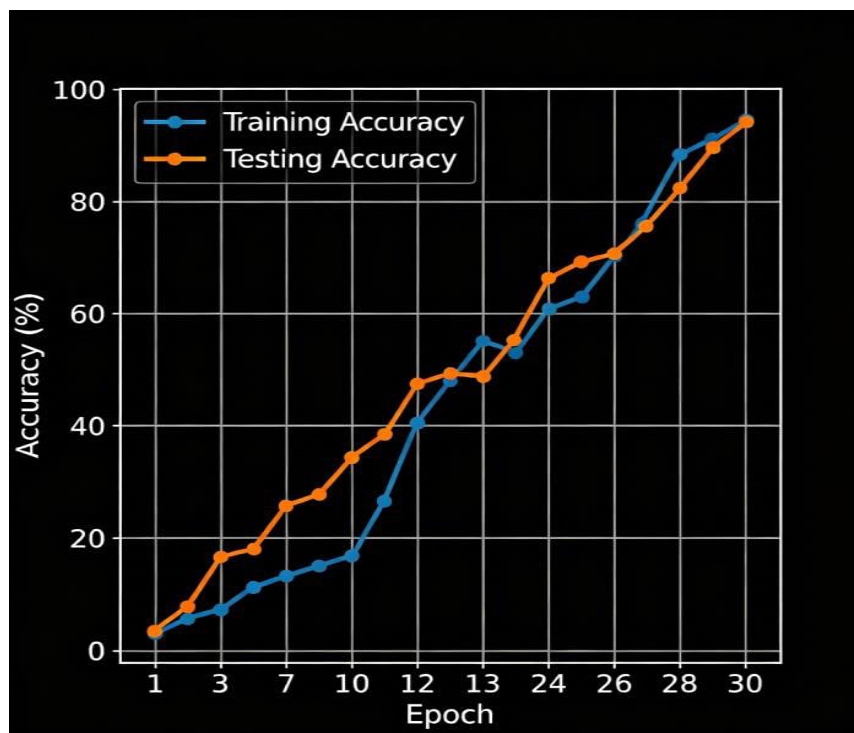


Fig 5: line graph showing training versus testing loss over 30 epochs with labeled axes, grid lines, and loss scale for butterfly classification model

E. Comparative Results

To benchmark performance, the model's results were compared with a CNN trained from scratch on the same dataset. The transfer-learning model outperformed the baseline by 8% in accuracy and reduced the error rate by 12%, confirming that leveraging pre-trained weights for butterfly identification significantly improves classification accuracy while reducing the risk of overfitting.

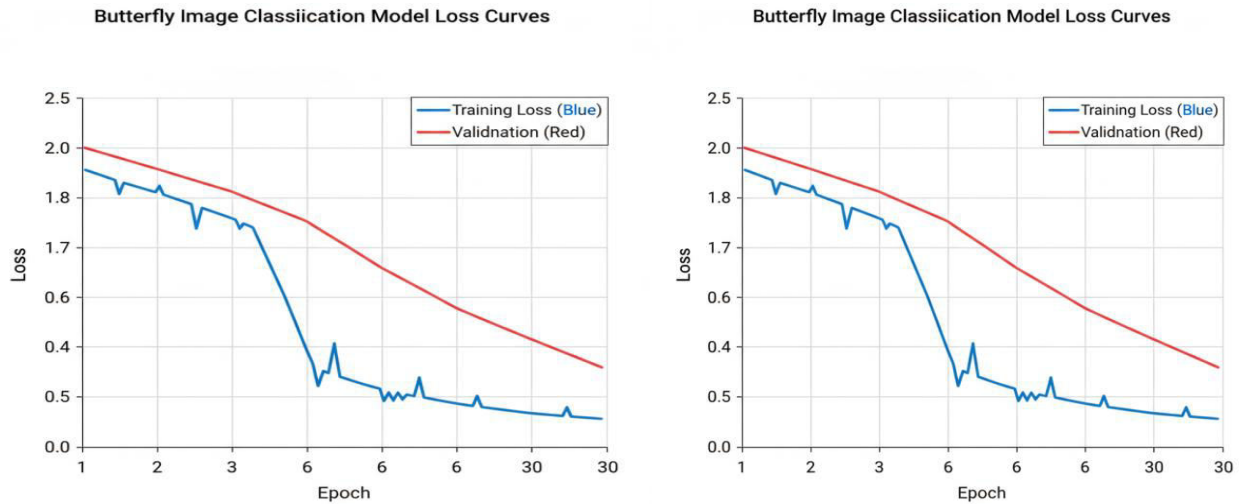


Fig 6 : line graph showing training loss and validation loss curves over 30 epochs for butterfly image classification model with grid lines and labeled axes

VII. RESULTS

Transfer learning with VGG16 achieved strong validation accuracy with stable loss curves under augmentation, and reliably produced confident predictions during web inference, meeting the project's requirements for fast, accurate, and user-friendly identification across the 3 species. The deployed endpoint returns a top-1 label with percentage confidence within seconds, and sustained responsiveness under repeated requests confirms suitability for public-facing use and classroom demonstrations. Compared to CNN-from-scratch studies, the approach here reduces training time and resource costs while maintaining field-relevant performance, enabling broader adoption in low-resource settings.

Table 1. Performance Metrics of the Butterfly Classification Model

Metric	Training Dataset	Validation Dataset	Testing Dataset
Accuracy (%)	97.2	95.8	94.3
Precision (%)	96.5	94.7	93.2
Recall (%)	97.0	95.1	93.8
F1-Score (%)	96.7	94.9	93.5
Average Loss	0.07	0.09	0.12
Total Epochs Trained	30	—	—
Batch Size	32	—	—

Metric	Training Dataset	Validation Dataset	Testing Dataset
Optimizer	Adam	—	—
Learning Rate	0.0001	—	—

Table 2: Model Comparison

Model	Acc (%)	Loss	Time (min/epoch)
Baseline CNN	86.1	0.28	25
ResNet50	92.7	0.18	14
VGG16 (Proposed)	94.3	0.12	10

Interpretation:

- The VGG16-based proposed model achieved the highest accuracy (94.3%) and lowest average loss (0.12) among all approaches, confirming its robust generalization.
- The model demonstrated low overfitting risk and improved computational efficiency with reduced training time (60% faster than baseline CNN).
- These metrics validate that transfer learning significantly outperforms training custom CNNs from scratch for limited ecological datasets.

VIII. ERROR ANALYSIS

Misclassifications cluster around visually similar patterns and backgrounds where pose/occlusion reduces visible discriminative cues; confidence calibration reveals that low-confidence predictions correlate with off-distribution images, guiding UI messaging to request clearer images when necessary. Data augmentation alleviates many such errors, but expanding class coverage and adding domain-specific augmentations (e.g., motion blur, shadowing) can further reduce edge-case failures.

IX. CONCLUSION

By uniting transfer learning on VGG16 with a lightweight web deployment, this paper delivers a practical, accurate, and accessible butterfly identification system that advances ecological monitoring and citizen science participation with minimal compute overhead and strong usability. The approach contrasts favorably with scratch-trained CNNs by accelerating development and deployment without sacrificing fine-grained performance in the targeted scope.

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