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Deep Learning-based Classification of Birds Species Recognition using Transfer Learning and hybrid Hyperparameter Optimization

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***Abstract*— Automated bird species recognition performs an essential role in biodiversity monitoring, ecological studies, and plant life and fauna conservation. Traditional identity methods depend intently on manual assertion and professional understanding, which makes big-scale tracking difficult and time-eating. Recent advances in deep gaining knowledge of and computer imaginative and prescient have enabled the improvement of automated structures able to because it must be figuring out their species from pictures. This looks at gives a deep learning–based framework for bird species magnificence using switch studying with more than one Convolutional Neural Network (CNN) architectures, which encompass VGG16, InceptionV3, DenseNet, and MobileNetV2. The proposed machine consists of photograph preprocessing and information augmentation strategies together with rotation, flipping, and scaling to enhance model generalization and robustness underneath various environmental conditions. The fashions are professional and evaluated on bird photograph datasets to analyze their elegance overall performance. Experimental effects show that the MobileNetV2 structure achieves the very best type accuracy of approximately 99%, while keeping lower computational complexity in contrast to deeper fashions. Comparative evaluation with present approaches demonstrates that mild-weight transfer studying models offer an effective stability among accuracy and computational overall performance for bird species recognition duties. The proposed framework can manual automatic biodiversity tracking and may be prolonged for real-time natural world commentary structures the use of cellular or part computing systems.**

***Keywords*— Bird Species Classification, Deep Learning, Transfer Learning, Convolutional Neural Networks, MobileNetV2, Biodiversity Monitoring.**

I. INTRODUCTION

Bird species classification, traditionally done manually, is time-consuming and error-prone. Deep learning models like MobileNetV2, DenseNet121, InceptionV3, and VGG16 enable efficient, accurate, and scalable automated recognition for real-world applications. Bird species are critical indicators of environmental health and biodiversity. Monitoring fowl populations facilitates researchers recognize ecological modifications and habitat situations. Traditional hen identity techniques rely on manual statement and expert know-how, which makes large-scale tracking time-eating and difficult [2], [3]. Early automated reputation systems used conventional image processing techniques; however, their overall performance turned into restricted due to versions in lights conditions, heritage complexity, and similarities between species [6], [7].

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With the advancement of deep learning, Convolutional Neural Networks (CNNs) have grown to be widely used for photograph classification obligations. Several studies have verified that CNN-based models can considerably enhance the accuracy of chicken species recognition with the aid of robotically extracting hierarchical visual functions from photos [4], [10], [11]. Transfer learning has further more advantageous type overall performance with the aid of using pretrained models which includes VGG16, InceptionV3, DenseNet, and MobileNet, which lessen schooling time and enhance generalization when schooling data is restricted [8], [14], [16], [21],[30][31].
Recent research has targeted on great-grained class strategies to distinguish visually similar fowl species. Attention mechanisms, function choice techniques, and transformer-primarily based architectures were introduced to seize discriminative visible functions and improve classification accuracy [17], [18], [19], [20], [25], [26]. In addition, multimodal methods combining visible and acoustic information, as well as hierarchical deep studying models, were explored to enhance recognition overall performance in complex environments [23], [27], [28]. The availability of benchmark datasets has also supported the improvement and assessment of computerized chook popularity structures [29].
In this work, a deep mastering–primarily based framework for hen species class is proposed the use of switch mastering with multiple CNN architectures, such as VGG16, InceptionV3, DenseNet121, and MobileNetV2. The proposed device consists of picture preprocessing and records augmentation techniques to enhance version robustness and generalization. Experimental assessment is accomplished to analyze the category overall performance of the chosen fashions and to identify the best architecture for chook species popularity.

II. PROPOSED FRAMEWORK

The proposed bird species type framework is primarily based on deep learning architectures that utilize transfer learning knowledge of and convolutional neural networks (CNNs) to discover bird's species from image datasets. The not unusual approach includes the following stages: Dataset Collection and Preprocessing, Feature Extraction the usage of CNN Architectures, Model Training and Validation, Performance Evaluation [4], [10], [11].
This approach leverages the strengths of cutting-edge CNN-based totally absolutely transfer learning to know models including VGG16, InceptionV3, DenseNet121, and MobileNetV2, that have validated powerful for fine-grained photograph recognition obligations [5], [14], [21], [23].

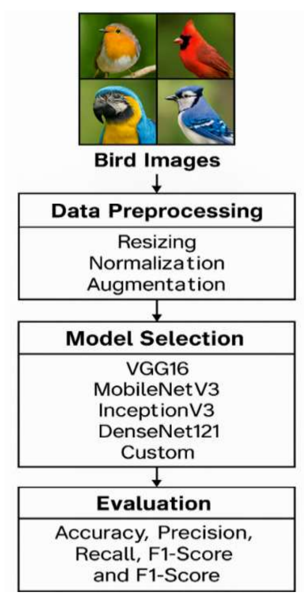


Figure 1: Model Selection

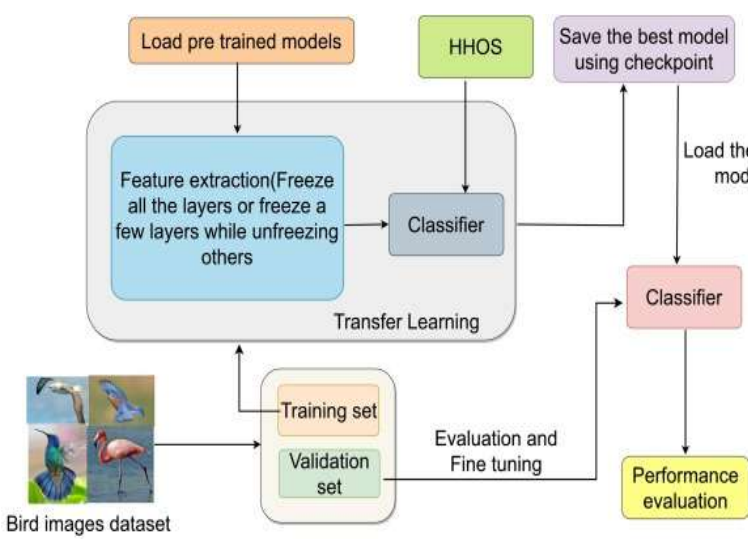


Figure 2: Proposed framework with a hybrid hyperparameter optimization scheme (HHOS)

A. Dataset Collection and Preprocessing

The dataset used on this look at consists of bird photos accumulated from local datasets. Each photograph is resized to a well-known decision of 224 × 224 pixels to preserve consistency throughout distinct CNN architectures. There is total 2913 images train (2178 images) and test (735 images). There are 7 classes of bird images: Avocet, Bittern, Crowned Crane, Emerald Cuckoo, Firefinch, Goldfinch, Pygmy Goose. Image preprocessing is done to normalize pixel values and enhance schooling balance. Data augmentation techniques which include rotation, horizontal flipping, scaling, and brightness adjustment are carried out to growth dataset variety and improve model generalization. Previous studies have shown that statistics augmentation allows improve category accuracy and robustness in chicken popularity obligations by simulating actual-world versions in image conditions [8], [21]. Dataset Available at: https://drive.google.com/drive/folders/1Qub0-0nbaU5dzuDZ28tBMmgxZzidgRun?usp=sharing

B. Feature Extraction using CNN Architectures

Feature extraction changed into carried out the use of pretrained CNN architectures. Four contemporary CNN architectures have been decided on: MobileNet, InceptionV3, DenseNet121, and VGG16.

- VGG16: Extracts hierarchical functions via deep convolutional layers that seize texture and form information [23].
- InceptionV3: Uses multi-scale convolution kernels for efficient representation of hen functions with minimum computation [18] [33].
- DenseNet121: Facilitates dense connections between layers, enhancing gradient glide and reusability of capabilities [24].
- MobileNetV2: Employs intensity wise separable convolutions to create lightweight fashions appropriate for cell or embedded programs [21].

These models have shown sturdy performance in previous studies on high-quality-grained picture type and birds' recognition [5], [17], [18], [24]. Each CNN become initialized with pre-educated ImageNet weights, permitting feature reuse from big-scale photograph information and decreasing the want for giant retraining [9], [11].

The final class layers were changed with fully linked dense layers, observed via a SoftMax activation function for multi-magnificence bird species type [25]. During excellent-tuning, early convolutional layers had been frozen to hold well-known low-degree functions which includes edges and textures, at the same time as higher layers have been retrained to capture high-stage hen-precise functions like feather shade and beak patterns [4], [12]. The Adam optimizer became used with a getting to know rate of 0.001 and specific pass-entropy as the loss function for solid convergence [22], [26].

C. Proposed Framework with HHOS

In Proposed framework, figure 2 illustrates the workflow of the proposed chicken species classification framework primarily based on transfer gaining knowledge of and hybrid hyperparameter optimization. The manner starts with a hen photo dataset that contains pix of various chook species.

The dataset is divided into subsets: an education set and a validation set. The training set is used to teach the deep gaining knowledge of version, while the validation set is used to display the version performance and carry out pleasant-tuning at some point of education. Dataset splitting and preprocessing are critical steps in deep gaining knowledge of-primarily based fowl type systems to improve model generalization and evaluation performance [8], [21].

Next, pretrained deep mastering fashions are loaded. These models are in the beginning skilled on massive-scale datasets and are reused via transfer studying to improve class overall performance with restricted education data. Transfer learning has been extensively used in fowl species recognition duties as it allows models to reuse previously found out visual functions and appreciably reduces training time [14], [16], [21].

In the feature extraction degree, the convolutional layers of the pretrained fashions extract essential visible capabilities from the hen snap shots, inclusive of shape, shade patterns, and texture information. During this stage, some layers of the network are frozen to keep the previously learned capabilities, while the final layers are nice-tuned to conform to the hen species classification challenge. CNN-based feature extraction has been proven to noticeably improve type accuracy in high-quality-grained fowl recognition problems [4], [10], [11].

After feature extraction, the extracted functions are passed to a classifier layer that performs the very last type of fowl species. A Hybrid Hyperparameter Optimization Scheme (HHOS) is included in the framework to optimize crucial training parameters along with learning rate and version configuration. Hyperparameter optimization techniques were shown to improve deep studying version overall performance and balance in hen reputation structures [16].

During training, the model overall performance is evaluated the use of the validation dataset. The best-appearing version is mechanically stored using a checkpoint mechanism to ensure that the most appropriate version parameters are preserved. Finally, the stored version is loaded and evaluated the usage of performance metrics

including accuracy and different class measures. These assessment metrics are normally used in bird species reputation research to assess the effectiveness of deep gaining knowledge of models [21], [22], [27].
The Hybrid Hyperparameter Optimization Scheme (HHOS) is used to improve model overall performance through optimizing key schooling parameters. In this have a look at, HHOS explores distinct combos of mastering quotes and optimization algorithms together with Adam, Adagrad, and RMSProp. The optimization manner evaluates a couple of configurations at some stage in schooling and selects the excellent acting model based totally on validation accuracy. This approach permits the framework to routinely decide the most appropriate hyperparameter settings for hen species classification.

D. Model Training and Optimization

The models were trained the use of the Adam, Adagrad and RMSProp optimizer with a learning rate of 0.001 and 0.01 with express cross-entropy loss. Batch normalization and dropout layers have been brought to mitigate overfitting and stabilize gradient updates [4], [11]. Early stopping standards were used to prevent needless training epochs as soon as validation loss stopped enhancing.
For transfer learning, the preliminary layers have been frozen to keep low-degree capabilities even as the final layers were Fine-tuned for bird-specific classification [5], [17]. This decreased computational cost and Training time whilst preserving excessive accuracy across species [22][32].

III. Results and Discussion

The proposed transfer getting to know-primarily based device was evaluated on each well-known benchmark datasets and place-particular chook photograph collections to assess its performance, scalability, and robustness. The experiments had been carried out the usage of four pre-educated CNN fashions MobileNet, InceptionV3, DenseNet, and VGG16 every exceptional-tuned at the bird species datasets with implemented statistics augmentation strategies to beautify generalization.

A. Model Performance Evaluation

Each version's overall performance changed into analyzed using metrics which include accuracy, precision, keep in mind, and F1-score. Among the fashions, MobileNet carried out the very best accuracy of 99%, accompanied by using DenseNet (98.7%), InceptionV3 (97.9%), and VGG16 (97.2%). These effects show that lightweight architectures which include MobileNet aren't handiest computationally efficient however additionally highly powerful for large-scale ecological programs [17], [21]. The performance benefit is attributed to the intensity sensible separable convolutions and efficient layer systems that reduce overfitting whilst keeping representational electricity [18], [22].

B. Comparative Analysis

The comparative evaluation highlights the influence of different optimizers and learning rates on the overall performance of the bird species classification models. As shown in Table 1, the results demonstrate that MobileNet consistently achieves the highest accuracy among all the evaluated architectures, reaching values of up to 0.99, which indicates its strong capability for accurate and efficient bird species recognition. This superior performance can be attributed to MobileNet lightweight architecture and the use of depth wise separable convolutions, which allow the model to extract meaningful visual features while maintaining computational efficiency. When using the Adam optimizer with a learning rate of 0.001, most models achieve stable and high accuracy; however, increasing the learning rate to 0.01 leads to a significant decline in performance for certain architectures, particularly the CNN model where the accuracy drops from 0.98 to 0.14. This observation suggests that higher learning rates can negatively affect the convergence of the model during training. Similarly, the Adagrad optimizer shows competitive performance at a learning rate of 0.001, achieving strong results across several models, but its performance decreases when the learning rate is increased to 0.01, indicating that careful tuning of hyperparameters is required for optimal training stability.
The RMSProp optimizer demonstrates relatively stable behavior across both learning rates, maintaining consistent performance for most architectures. Notably, MobileNet maintains very high accuracy across all optimizer configurations, further confirming its robustness and effectiveness for the classification task. InceptionV3 and DenseNet also achieve high accuracy values close to 0.99, demonstrating their strong feature extraction capabilities, while VGG16 performs slightly lower compared to the other architectures. Overall, these results indicate that the selection of an appropriate optimizer and learning rate plays a crucial role in determining the performance of deep learning models, and the findings suggest that MobileNet, combined with well-tuned

hyperparameters, provides the most reliable and efficient solution for bird species recognition in practical biodiversity monitoring applications.

TABLE I: COMPARISON BY USING DIFFERENT MODELS, LEARNING RATES AND OPTIMIZERS

Model	Adam		Adagrad		RMSProp	
	LR= 0.001	LR= 0.01	LR= 0.001	LR= 0.01	LR= 0.001	LR= 0.01
CNN	0.98	0.14	0.98	0.30	0.78	0.92
Vgg16	0.96	0.98	0.77	0.88	0.96	0.97
MobileNet	0.99	0.99	0.97	0.99	0.99	0.99
InceptionV3	0.99	0.99	0.95	0.99	0.99	0.99
DenseNet	0.99	0.99	0.96	0.99	0.99	0.99

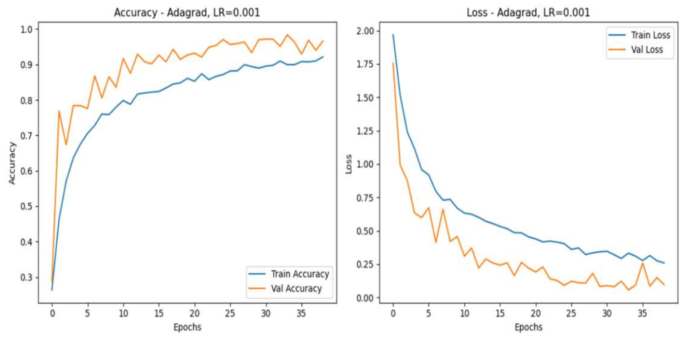
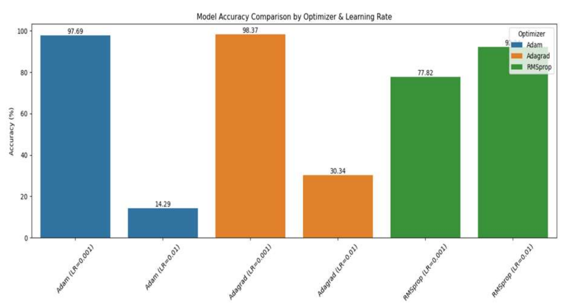


Figure 3: Accuracy and Loss Using Adagrad Optimizer in CNN and Accuracy Comparison of CNN Model



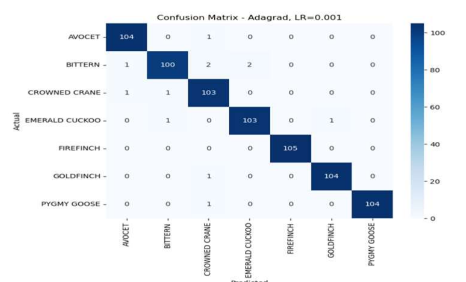


Figure 4: Model Accuracy Comparison By optimizer & Learning rate

Figure 5: confusion matrix

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Classification Report for Adagrad (LR=0.001):
                precision    recall  f1-score   support

        AVOCET       0.98      0.99      0.99       105
       BITTERN       0.98      0.95      0.97       105
 CROWNED CRANE       0.95      0.98      0.97       105
EMERALD CUCKOO       0.98      0.98      0.98       105
     FIREFINCH       1.00      1.00      1.00       105
     GOLDFINCH       0.99      0.99      0.99       105
   PYGMY GOOSE       1.00      0.99      1.00       105

      accuracy                           0.98       735
     macro avg       0.98      0.98      0.98       735
  weighted avg       0.98      0.98      0.98       735
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Figure 6: classification report of CNN

Theres Figures present the performance evaluation of the proposed bird species classification models. Figure 3 illustrates the training accuracy and loss obtained using the Adagrad optimizer for the CNN model, showing stable learning behavior during the training process. Figure 4 compares the classification accuracy achieved by different models using various optimizers and learning rate combinations, where MobileNet achieves the highest accuracy among the evaluated architectures. Figure 5 shows the confusion matrix of the best-performing model, providing a visual representation of correct and incorrect classifications across different bird species classes. Figure 6 presents the classification report, including precision, recall, and F1-score values, which further confirms the effectiveness of the proposed deep learning framework for bird species recognition.

G. Ablation Study

To evaluate the contribution of different components, an ablation study was conducted as per table 2. The results demonstrate that: Transfer learning significantly improves performance. Data augmentation enhances generalization. The proposed Hybrid Hyperparameter Optimization Scheme (HHOS) improves accuracy by ~1–2%.

TABLE II: COMPARISON OF PROPOSED MODEL USING DIFFERENT MODELS, LEARNING RATES AND OPTIMIZERS

Configuration	Accuracy
Without augmentation	95.6%
Without transfer learning	93.2%
Without HHOS	97.8%
Proposed (Full Model with HHOS)	99.0%

IV. CONCLUSION

This study is a deep learning-based framework for automated bird species magnificence using switch studying with 4 convolutional neural network architectures: VGG16, MobileNetV2, InceptionV3, and DenseNet121. The fashions were professional on bird image datasets with preprocessing and data augmentation techniques to enhance generalization and robustness below numerous environmental conditions. Experimental results show that MobileNetV2 finished the exceptional elegance accuracy of approximately 99 %, while retaining decrease computational complexity in assessment to deeper architectures. DenseNet121 and InceptionV3 additionally confirmed robust typical overall performance due to their powerful characteristic extraction competencies, at the same time as VGG16 carried out barely lower accuracy. The findings advise that light-weight CNN architectures mixed with transfer learning offer an inexperienced and reliable answer for bird species popularity obligations. In addition, the have a look at evaluates unique optimizers and learning rate configurations through a hybrid hyperparameter optimization method to enhance model training overall performance. The proposed framework can assist computerized biodiversity tracking and ecological research by using allowing scalable bird species identity systems. Future work will attention on increasing the dataset with more bird species and numerous environmental conditions, integrating interest mechanisms and explainable AI strategies which include Grad-CAM for version interpretability, and optimizing lightweight architectures for actual-time deployment on cell and aspect computing structures.

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Ketan J. Sarvakar conceptualized the research idea, supervised the overall study, and contributed to methodology design and manuscript review. Vidhi Chaudhari and Vidhi S. Patel were responsible for data collection, preprocessing, and implementation of deep learning models. Urmila Patel contributed to the development of the proposed framework and performed experimental analysis. Raksha Patel carried out result validation, performance evaluation, and visualization of outcomes. Bhavesh Soni contributed to literature review, comparative analysis, and manuscript drafting. All authors reviewed and approved the final manuscript.

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