International Journal of Scientific Research & Engineering Trends
Volume 12, Issue 3, May-Jun-2026, ISSN (Online): 2395-566X

Automated Classification of Reptiles and Amphibians Using MobileNetV2 and Transfer Learning

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Abstract- — This article presents a new approach to automated amphibian and reptile categorization that makes use of deep Convolutional neural networks (CNNs) and transfer learning. By developing a reliable and precise MobileNetV2 model for species identification using deep learning, we tackle the limitations of traditional classification methods while also acknowledging the ecological importance of these two vertebrate groups. Using a transfer learning approach on a massive collection of amphibian and reptile images, we train a pre-trained Convolutional neural network (CNN) to overcome the issue of small dataset size. The model is able to generalize well across several species due to its high extraction efficiency. Additionally, the article delves into the significance of image augmentation techniques for enhancing model performance, particularly in cases when labeled data is scarce. Results are favorable when the proposed method is used to overcome challenges caused by changes in size, posture, and environmental factors. Ecological monitoring, conservation efforts, and biodiversity surveys might benefit from the model's classification accuracy, which we prove by comparing it to a large dataset of amphibians and reptiles. With an accuracy rate of 82%, the proposed MobileNetV2 model cans correctly categories amphibians and reptiles. The growing field of computer vision as it pertains to animal ecology and biology has a scalable and successful approach to automated species identification, which this work adds to it. The results show that deep learning techniques particularly transfer learning, have the potential to address the issues with animal categorization. Additional investigation on the connection between AI and biodiversity protection might result from this.

Keywords: Artificial Intelligence, DeepLearning, Reptiles and Amphibians Classification Analysis, Model Training, MobileNetV2.

I. INTRODUCTION

The group of animals known as herpetofauna, which includes both amphibians and reptiles, is a crucial and diverse part of the world's biodiversity. Their unique ecological functions, which include anything from nutrient cycling to pest management, highlight how crucial it is to comprehend and preserve these species. Conventional techniques for identifying and tracking amphibians and reptiles sometimes rely on labor-intensive field surveys,

Isolated or difficult-to-reach environments. The use of computer vision and machine learning technologies is a promising way to increase the effectiveness and precision of species identification as these technologies continue to transform ecological research. Deep learning methods, and more especially Deep Convolutional Neural Networks (CNNs), have shown impressive results in a number of image identification applications in recent years.

As a subset of deep learning, transfer learning entails using huge datasets of pre-trained models to improve the performance of models learned on smaller, domain-specific datasets. Transfer learning combined with CNNs is an appealing strategy for automated herpetofauna identification, since it has shown to be very successful in handling picture classification issues. This work explores the field of herpetology with the goal of creating a reliable and precise model for the categorization of amphibians and reptiles using Deep CNNs and Transfer Learning.

Given the inherent difficulties in differentiating various species owing to differences in size, color, and environmental context, deep learning techniques have the potential to transform the field. This research aims to address the drawbacks of conventional classification techniques by utilizing the enormous computing capacity of neural networks, providing a scalable and effective solution for species identification.

This study's main goals are to assess how well Transfer Learning adapts pre-trained CNNs to the task of classifying herpetofauna, evaluate the model's performance on a wide range of species, and examine how image augmentation techniques improve the model's capacity to generalize to various environmental conditions. By addressing the urgent problems in monitoring and controlling reptile and amphibian populations using technology, we want to add to the expanding corpus of research at the nexus of artificial intelligence and biodiversity protection.

II. LITERATURE REVIEW

While Tan, W.C. et al. [1-2] suggested strong links between common response variables and sampling approaches, they failed to find any between the various types of habitat fragmentation. Fraser, M. et al. [3-4] describe the status of every amphibian and reptile species found in the Cape of Good Hope Nature Reserve, which is located in the southern part of Table Mountain National Park. Abdullah, S.S. et al. [5-6] compiled a literature study of Mindanao's amphibians and reptiles. Using three general circulation models and two representative concentration routes (RCPs), Inman, R.D. et al. [7-8] portrayed several future habitat potential scenarios and identified study species that might be most affected by the changes anticipated under each climatic scenario. Important for both veterinary care and amphibian and reptile conservation efforts, three noteworthy fungal EIDs involving keratin trophism were documented by Schilliger, L. et al. [9–10]. In order to determine the herpetofauna of Uruguay's susceptibility to CC, Vaz-Canosa, P. et al. [11, 12] adapted a worldwide trait-based technique and applied it to the country on a national scale. In order to reduce herpetofauna conflicts near global traffic networks, Aburrow, K. et al. [13–14] reviewed the most current publicly available best practice recommendations for fencing.

Shortly said, metabolites are the byproducts or intermediates of certain substrates' biotransformation as they go through metabolic pathways (Clarke, S. et al., 2015: 15-16). The variety of amphibians and reptiles in PNLT (Parque Nacional Laguna del Tigre) was thoroughly studied by Gryphon, R.K. et al. In addition, they assessed the degree of endemism and diversity among these species [17–18]. Park area, diversity of wetland habitats, and connectivity were shown to be associated with amphibian and reptile species richness, which in turn decreased prediction error by around 50% compared to a null model, according to research by Marsh, D.M. et al. [19–20]. Using deep learning capabilities, the Deep Convolutional Neural Networks (CNNs) and Transfer Learning technique classifies amphibians and reptiles, taking into account the unique challenges of herpetofauna identification.

Here are the key steps to take while following the proposed method: Optimizing contrast, noise reduction, and image size using preprocessing techniques to guarantee consistency throughout the dataset. Retraining the model on the herpetofauna dataset with the pre-trained layer weights frozen could help the network adapt to the new task by using the knowledge obtained from the bigger dataset. Using the herpetofauna dataset to fine-tune the model's performance and conform it to the nuances of reptile and amphibian traits. By addressing issues related to size, lighting, and posture, data augmentation methods may artificially increase the dataset's diversity. Using a separate validation dataset, we test the model's ability to generalize to new data and ensure dependable performance in real-world scenarios. To show how deep learning has improved things, we'll compare the proposed CNN-based model to baseline methods, such as traditional machine learning classifiers.

It is possible to visualize the learned qualities to provide insight into which amphibian and reptile morphological features are most crucial for the model's decision-making. Methodically using these processes, the proposed technique aims to provide a robust and flexible model for the automated classification of amphibians and reptiles, thereby promoting technology-driven solutions in biodiversity study and conservation. There are a lot of subtopics in the research. In Section 3, we focus on the input dataset. The fourth portion focuses on the analysis of computing error rates. The focus of Section 5 is on training the MobileNetV2 model. Section 6 mostly addresses the results section. Section 7 mostly covers the references and the conclusion.

III. INPUT DATA SET

An important factor in how well a machine learning model works is the quality and diversity of the dataset used as input.

Fig. 1. Dataset Image of (a) Chameleon (b) Crocodile (c) Frog (d) Gecko (e) Iguana (f) Lizard (g) Salamander (h) Snake (i) Toad (j) Turtle

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In the realm of deep learning in particular. To construct a robust and adaptable model for amphibian and reptile classification using Deep Convolutional Neural Networks (CNNs) and Transfer Learning, the input dataset is of utmost importance. If the input dataset is properly chosen to account for these parameters, the model may be trained to recognize the great variety of amphibians and reptiles. A trustworthy and efficient system for field-based automatic species categorization may be established using this. Fig. 1 shows that the dataset is sourced from the free and open-source Kaggle platform.

IV. COMPUTING ERROR RATE ANALYSIS

Critical to determining a classification model's efficacy is error rate analysis. Specifically, models that detect amphibians and reptiles using Deep Convolutional Neural Networks (CNNs) and Transfer Learning are subject to this reality. In order to conduct this research, many metrics are calculated that provide insight into the model's accuracy, precision, recall, and overall efficacy. Scholars and professionals may have a better understanding of the benefits and downsides of the proposed strategy by carefully calculating these error rate indicators and conducting a thorough evaluation. Important for enhancing the model's performance in real-world scenarios, optimizing its hyper parameters and ultimately developing reliable tools for reptile and amphibian species identification (Fig. 2), this data is essential.

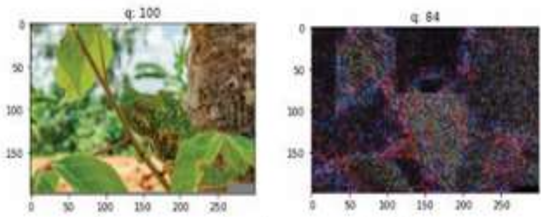

Fig. 2. Computation of Error Rate Analysis

V. TRAINING THE MOBILE NET V2 MODEL

Because of its famed lightweight architecture and efficiency, MobileNetV2 is a popular choice for image classification jobs, especially in scenarios where computational resources are limited. There are many important steps in training the MobileNetV2 model to classify amphibians and reptiles using Deep Convolutional Neural Networks (CNNs) and Transfer Learning. Researchers may be able to make better use of the MobileNetV2 architecture for reptile and amphibian classification with the help of transfer learning. The transfer learning approach makes MobileNetV2 more adaptable to the specific features of the target dataset, and its lightweight design makes it suitable for deployment in environments with restricted resources. This is seen in Figure 3.

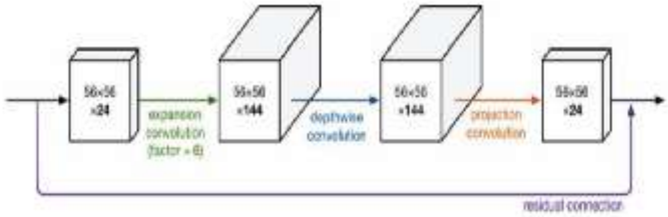

Fig. 3. MobielNetV2 Model Architecture

VI. RESULTS

Period Determination for Categorization For deep learning model training, deciding on an appropriate number of training epochs is a key factor, particularly when dealing with amphibian and reptile classification utilizing transfer learning. How often the model runs through the training dataset is dependent on the epoch count. Each complete run of the training dataset is called an epoch. Finding the sweet spot between avoiding over fitting and keeping the model convergent is key to getting the optimal number of epochs. Scientists may improve the transfer learning model's performance in amphibian and reptile classification by carefully examining these factors and gradually changing the amount of training epochs. The objective, as seen in Figure 4, is to strike a compromise between the model's memorization of noise and the presentation of relevant information from the dataset. Signs of over fitting while still letting it learn

Epoch	Training Loss	Training Accuracy	Validation Loss	Validation Accuracy
1	2.3390	0.1642	2.0534	0.3402
10	0.9544	0.7141	0.8894	0.7415
20	0.6642	0.7753	0.6583	0.7911
30	0.5625	0.8064	0.6065	0.8056
40	0.5007	0.8296	0.5861	0.8108
50	0.4568	0.8482	0.5756	0.8201
60	0.4101	0.8604	0.5683	0.8170
70	0.3698	0.8715	0.5647	0.8180

Fig. 4. Epoch Calculation Depiction

B. Precision in Validation and Training Keeping an eye on the accuracy of training and validation is essential for assessing the performance and generalizability of a deep learning model as it is being trained. This is particularly true when dealing with amphibian and reptile categorization utilizing Deep Convolutional Neural Networks (CNNs) and Transfer Learning. Training accuracy is defined as the proportion of instances in the training dataset that were properly

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categorized. Over the course of many epochs, the model's training accuracy often rises, showing that it can detect and remember patterns in the training data. However, a high training accuracy is insufficient to guarantee that the model would effectively classify freshly found data. Training on a separate dataset allows the model to avoid seeing the validation accuracy dataset. This dataset is used as a stand-in to test the model's generalization performance.

It is critical to monitor validation accuracy in order to detect over fitting, a situation where the model becomes highly specialized in the training set and fails to perform well on new, diverse cases. In order to make educated decisions about a model's convergence, generalizability, and potential issues like over fitting or under fitting, researchers should consistently monitor and analyze the model's accuracy throughout training and validation. By repeatedly refining the model until it achieves optimum performance in amphibian and reptile classification, as seen in Fig. 5, this iterative process aids in building a trustworthy and effective deep learning system.

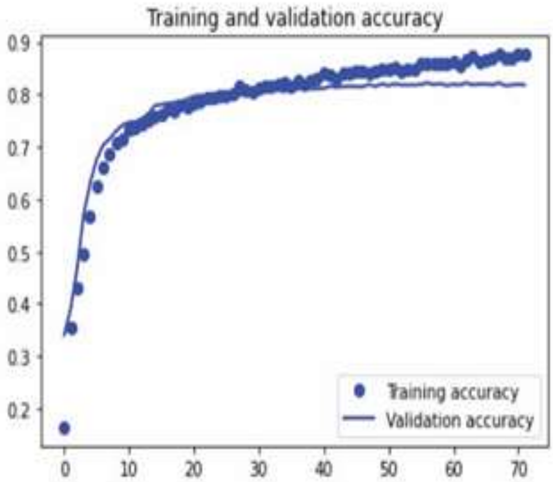

Fig. 5. Training and Validation Accuracy

Part C: Mistakes in Training and Validation a key component of training deep learning models for reptile and amphibian categorization using Transfer Learning and Deep Convolutional Neural Networks (CNNs) is monitoring training and validation loss.

By measuring the discrepancy between the model's predicted output and the real labels, loss functions provide a practical way to evaluate the model's ability to understand the underlying patterns in the data. The training loss is the discrepancy or error between the model's predicted labels and the actual labels in the training dataset. The goal of training is to minimize this loss, which means that the model is improving at recognizing the features and patterns that are exclusive to amphibian and reptile images. As training progresses over epochs, the training loss often decreases. Calculating validation loss requires using a separate dataset that was not available to the model during training.

You may evaluate the model's generalizability with the use of this dataset, which stands in for unobserved data, by monitoring validation loss. The model may be over fitting and unable to generalize to new samples if the validation loss increases or hits a plateau while the training loss remains flat. By carefully monitoring and assessing training and validation loss, researchers may get a better understanding of the model's learning processes. By iteratively adjusting the model architecture and hyper parameters, a deep learning system can be trained to classify amphibians and reptiles efficiently and with good generalizability (Fig. 6).

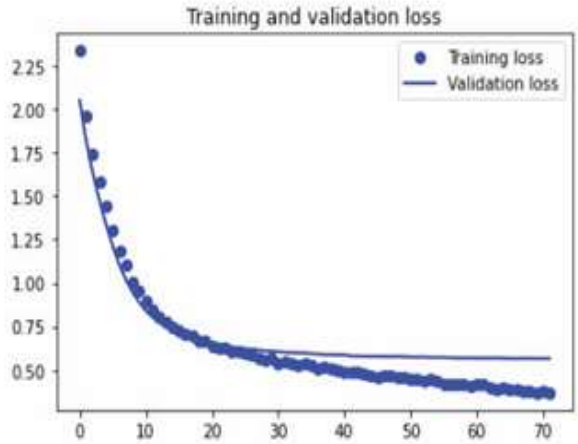

Fig. 6. Training and Validation Loss

D. Classification Report Plotting Classification reports are helpful for assessing a model's efficacy as they provide an in-depth evaluation of metrics like as recall, accuracy, and F1 score for every class. Using Deep Convolutional Neural Nets (CNNs) and Transfer Learning to classify amphibians and reptiles, these reports provided give a detailed visual representation of the model's ability to correctly identify different species. In order to have a better understanding of how well the deep learning model performed across all reptile and amphibian dataset classes, researchers and practitioners may examine the classification results visually. Figure 7 shows how this visual representation aids in decision-making, communication, and the model's accuracy and generalizability being improved iteratively.

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	precision	recall	f1-score	support
Chameleon	0.74	0.69	0.72	49
Crocodile_Alligator	0.93	0.93	0.93	136
Frog	0.71	0.65	0.68	97
Gecko	0.64	0.52	0.57	54
Iguana	0.70	0.76	0.73	91
Lizard	0.62	0.52	0.57	94
Salamander	0.86	0.88	0.87	97
Snake	0.88	0.95	0.91	112
Toad	0.68	0.69	0.69	107
Turtle_Tortoise	0.94	0.97	0.95	372
accuracy			0.82	1209
macro avg	0.77	0.76	0.76	1209
weighted avg	0.82	0.82	0.82	1209

Figure 7. Report on Classification using MobileNetV2 Model

E. Controversy Matrix Plotting To evaluate a classification model's performance, one useful tool is the confusion matrix, which provides an in-depth examination of each class's true positive, true negative, false positive, and false negative predictions.

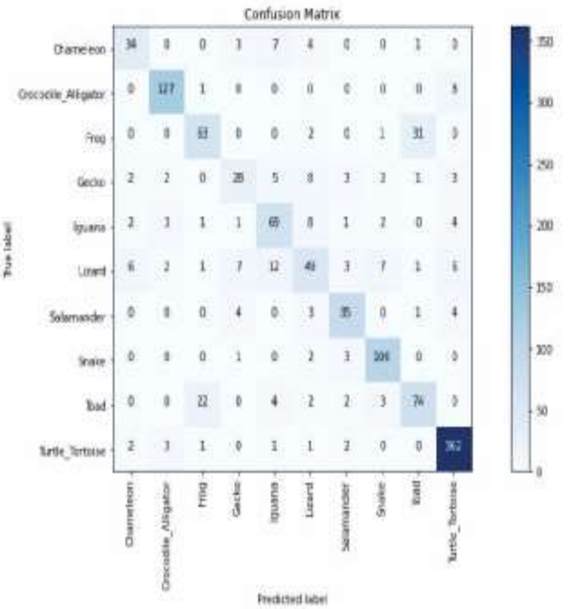

Fig. 8. Confusion Matrix for Classification on MobileNetV2 Model

When applied to the classification of amphibians and reptiles using Deep Convolutional Neural Networks (CNNs), plotting the confusion matrix gives a comprehensive visual representation of the model's ability to correctly classify different species. By seeing the confusion matrix, researchers may get a good idea of how well the deep learning model classified amphibians and reptiles. The data shown in Figure 8 allow the model to be accurate, effective, and refined in practical applications, especially in ecological monitoring and biodiversity protection.

VII. CONCLUSION

Using Deep Convolutional Neural Networks (CNNs) and Transfer Learning, reptiles and amphibians can be classified, which is an important step forward in computer vision for biodiversity monitoring. The work demonstrates the efficacy of transfer learning in enhancing species identification accuracy in scenarios lacking labeled data by drawing on past knowledge from large datasets. The model's versatility, ease of adaptation to different species, and capability to manage variations in size, posture, and environmental conditions, as well as its strong feature extraction capabilities, demonstrate its promise for valuable applications in ecological study and conservation.

Thanks to advancements in machine learning, more accessible data, and innovations in technology, the future of reptile and amphibian classification using Deep Convolutional Neural Networks (CNNs) and Transfer Learning is looking favorable. We need further research into the ethical concerns raised by using deep learning models in conservation and environmental contexts. It will be critical to work towards reducing biases, keeping things open, and incorporating ethical standards into model construction if we want responsible and inclusive applications. Finally, the use of Deep CNNs and Transfer Learning to the classification of amphibians and reptiles is expected to lead to exciting new developments. When technological advancement, interdisciplinary collaboration, and heightened awareness of ethical concerns come together, we may build models for biodiversity monitoring and conservation efforts that are dependable, comprehensible, and widely applicable.

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