Ant Species Recognition Through Deep Learning and Computer Vision with Integrated Recommendation System

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Abstract– **Ants play a vital role in biodiversity, but traditional identification methods are often tedious and error-prone. This paper leverages deep learning and computer vision to enhance the accuracy and ease of ant species identification. We developed a framework using CNNs to classify fire ants, ghost ants, weaver ants, and little black ants. Our dataset of 7,334 images, sourced primarily from Google Images, was augmented to improve model generalization. We evaluated a base model alongside DenseNet121, EfficientNetB0, and MobileNetV2, using accuracy and loss metrics. Our approach shows the potential of combining deep learning with practical recommendation systems to improve ant species identification, contributing to both scientific research and biodiversity management.**

Keywords– Ant Species; Recognition; Deep Learning; Computer Vision; Recommendation System; CNN

I. INTRODUCTION

Ants are a varied group of animals with a wide range of behaviors and ecological roles. They are sometimes ignored, yet they play a crucial role in biodiversity [1]. Traditional ant species identification techniques have long been hampered by arduous procedures and a tendency toward mistakes [2]. Advances in deep learning and computer vision are leading to a paradigm shift in the field of species identification, which recognizes the need for a revolutionary approach [3]. In order to make the identification of ant species easier, our research is an attempt to leverage these technological advancements by combining them with a simple class-based recommendation system [4]. Through the integration of computer vision techniques with deep learning algorithms, our goal is to develop a strong framework that can effectively and easily classify different ant species[5]. Our methodology is based on a comprehensive approach that pulls from a range of sources. Our approach incorporates a dataset that is crucial for comprehending the ants, from extensive image dataset to some taxonomic literature. Our goal is to improve the quality and reliability of the identification process while simultaneously making the accuracy and efficiency better [6]. The identification process can be streamlined by the use of CNNs in order to automatically learn certain features from the images, which removes the requirement of manually feature extraction by hand [7]. Our process is predicated on an all-encompassing strategy that takes into account several sources. To improve our system's accuracy, we integrated a large image dataset. In order to provide trustworthy training data for our models, this collection contains high-resolution images of different ant species that have been annotated and augmented [8]. In order to increase our model's capacity to generalize unseen data and increase the dependability in practical applications, it is necessary to incorporate a variety of representative samples [9]. Furthermore, our goal is to offer options for possible species identification based on visual similarities and other learnt patterns by incorporating a class-based recommendation system. This approach provides insights into the characteristics that can differentiate various ant species, which can help with the correct identification while also acting as an instructional tool [10]. Our objective is to raise the accuracy and efficiency while also strengthening the identification process's quality and dependability [11]. This study offers a method of ant species identification and recognition by fusing together computer vision and deep learning capabilities with a recommendation system.[12].

II. METHODOLOGY

A. Dataset

Our custom dataset includes 7,334 images of four specific ant species: fire ants, ghost ants, weaver ants, and little black ants. These images are divided into three groups: training, validation, and testing sets. The training set contains 6,330 images, the validation set comprises 604 images, and the testing set includes 400 images. These species were specifically chosen to represent a diverse range of ant species that are commonly found in the Philippines. Primarily sourced from Google Images, this dataset encompasses a wide array of environmental contexts, ensuring a comprehensive representation of each species in various settings. Each image is carefully annotated with its corresponding species label, so that the model can learn to classify new, unseen images into one of the four ant species based on the patterns it learns from the labeled training data.

B. Image Pre-processing and Augmentation

Initially, we applied auto-orientation and resizing, standardizing images to a dimension of 640x640 pixels but decided to go with 150x150 pixels to reduce training time. Augmentation techniques were then employed, expanding the dataset further. These augmentations included horizontal and vertical flips, rotations in 90-degree increments, and random rotations within a range of -15 to +15 degrees. Additionally, we adjusted saturation and brightness levels by up to ±25% and ±15%, respectively. We also rescaled images to a range of [0,1], applying a shear range of 0.2, and a zoom range of 0.2. Finally, we introduced noise to each image, affecting up to 1% of its pixels. The augmentation process resulted in three output images for every training example, effectively multiplying the dataset size and enhancing its diversity, thereby enriching the training process for our classification model.

Figure B1: Sample Image of Fire Ant

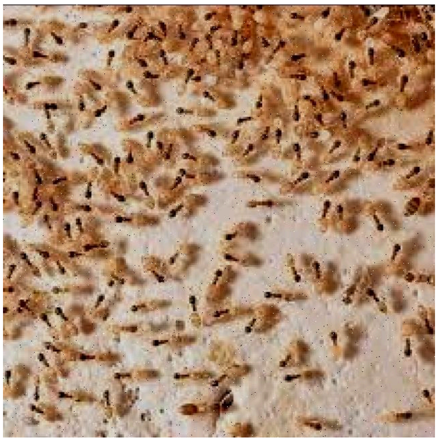

Figure B2: Sample Image of Ghost Ant

Figure B3: Sample Image of Little Black Ant

Figure B4: Sample Image of Weaver Ant

C. Visualization

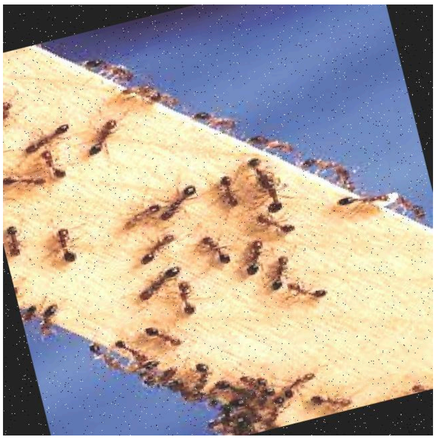

Figure C1: Sample Image of an Augmented Fire Ant Image

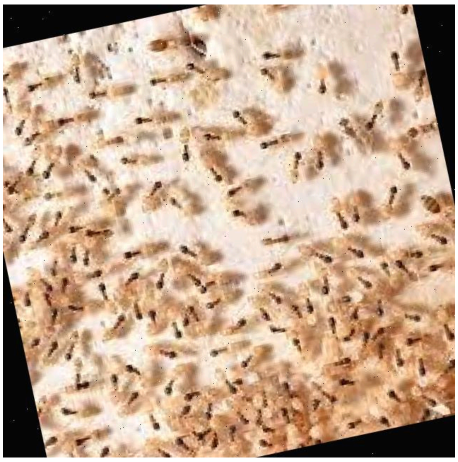

Figure C2: Sample Image of an Augmented Ghost Ant Image

Figure C3: Sample Image of an Augmente Little Black Ant Image

Figure C4: Sample Image of an Augmented Weaver Ant Image

As mentioned earlier, the dataset was augmented to increase its size. The augmentations involved horizontal and vertical flips, 90-degree rotations, and random rotations between -15 and +15 degrees. Additionally, we modified the saturation and brightness levels by up to ±25% and ±15%, respectively. Images were rescaled to a [0,1] range, with a shear range of 0.2 and a zoom range of 0.2. Finally, we added noise to each image, impacting up to 1% of the pixels.

D. Models

We employed a base model along with three additional models to compare and evaluate their performance. The base model utilized a sequential architecture with convolutional and pooling layers followed by fully connected layers. To compare the performance of our base model, we evaluated it against three other models:

DenseNet121: A convolutional neural network known for its densely connected layers. It is widely used in image classification tasks due to its efficient feature extraction capabilities.

EfficientNetB0: One of the members of the EfficientNet family, it offers a balance between model size and performance by scaling the depth, width, and resolution of the network

MobileNetV2: Designed for mobile and embedded vision applications, MobileNetV2 is a lightweight convolutional neural network architecture that emphasizes efficiency without compromising on performance.

E. Performance Evaluation Metrics

To evaluate the performance of our models across the training, validation, and test datasets. Two primary metrics, accuracy, and loss were used for this purpose.

Accuracy measures the proportion of correctly classified instances out of the total instances. It provides an overall indication of the model's correctness in predicting the classes of the images.

The higher the value of accuracy, the better its performance.

Loss quantifies the discrepancy between the predicted and actual values during training. It represents a measure of how well the model is performing, with lower loss values indicating better agreement between predicted and actual outcomes.

Training Data: Accuracy and loss metrics on the training data provided insights into how well the model was learning from the training examples. High accuracy and low loss on the training set indicate that the model is effectively capturing patterns and features in the data.

Validation Data: Performance metrics on the validation data allowed us to monitor the generalization capability of the model. Consistently high accuracy and low loss on the validation set suggest that the model is not overfitting to the training data and can generalize well to unseen data.

Test Data: Evaluation on the test data provided an unbiased assessment of the model's performance on new, unseen data. Accuracy and loss metrics on the test set helped confirm the model's effectiveness in real-world applications.

By utilizing accuracy and loss as performance evaluation metrics across the training, validation, and test datasets, we ensured a comprehensive assessment of our model's capabilities in classifying ant species accurately.

F. Recommendation System

In implementing our recommendation system, we've defined a set of recommendations corresponding to each ant species class identified by our model. These recommendations are tailored to address specific characteristics and behaviors associated with each species. The recommendations cover various aspects including handling precautions, control methods, and management strategies.

The delivery of the recommendation flows this way. Upon classifying an individual image or a batch of test images, our system retrieves the predicted class labels from the model's output. Using these labels, the system fetches the corresponding recommendations from the predefined set.

The recommendations are presented alongside the classification results, aiding users in understanding the implications of the identified ant species and suggesting appropriate actions or measures. This user-centric approach enhances the practical utility of our system, empowering users with actionable insights for effective ant species management and control.

III. RESULTS AND DISCUSSION

In this section, we present the results of our ant species classification model and discuss the implications of these findings. We evaluate the performance of our base model as well as three comparative models (DenseNet121, EfficientNetB0, and MobileNetV2) using accuracy and loss metrics across training, validation, and test datasets. Additionally, we provide insights into the effectiveness of our recommendation system in offering actionable advice based on the classification results.

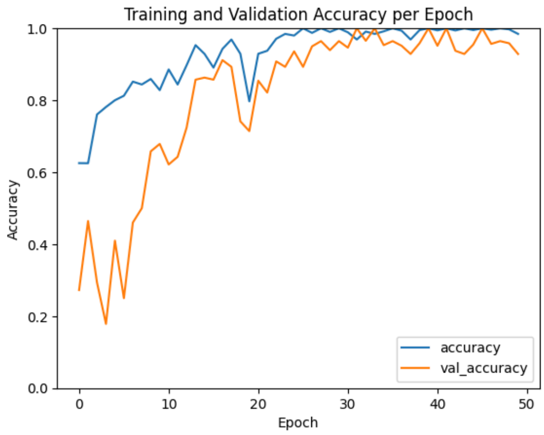

Figure 1: Base Model Training and Validation Accuracy Per Epoch

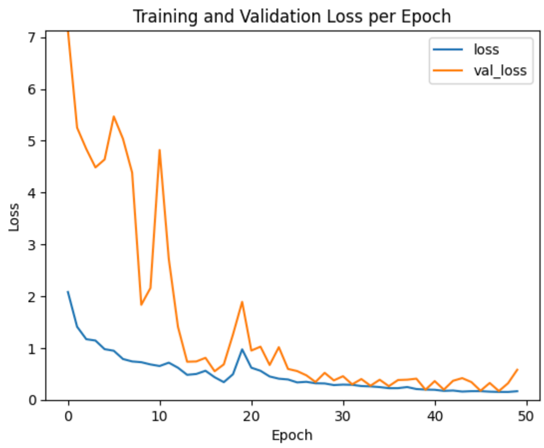

Figure 2: Base Model Training and Validation Loss Per Epoch

Our base model, designed with a sequential architecture, achieved notable performance in classifying the four ant species: fire ants, ghost ants, weaver ants, and little black ants. The performance metrics for the training, validation, and test datasets are summarized below.

Table 1: Performance Metrics of the Base Model

Base Model

Set	Accuracy	Loss
Training	98.44%	0.1655
Validation	92.86%	0.5791
Test	95.50%	0.3983

The base model achieved strong performance, with a training accuracy of 98.44% and a validation accuracy of 92.86%. The test accuracy reached 95.50%. The loss values were low, with 0.1655 for the training set, 0.5791 for the validation set, and 0.3983 for the test set. This indicates that the base model performed well in generalizing the data.

To provide a more detailed view of the base model's performance, we included the classification report and confusion matrices. Classification Reports provide detailed metrics (precision, recall, F1-score, support) for each class to understand the model's performance across different dimensions. Confusion Matrix shows the counts of actual vs predicted classifications, highlighting areas where the model is performing well and where it is making errors.

Classification Report:

	precision	recall	f1-score	support
fire-ant	0.91	0.96	0.93	100
ghost-ant	0.98	0.96	0.97	100
little-black-ant	0.96	0.96	0.96	100
weaver-ant	0.98	0.94	0.96	100
accuracy			0.95	400
macro avg	0.96	0.95	0.96	400
weighted avg	0.96	0.95	0.96	400

Figure 3: Classification Report for the Base Model

The classification report for the base model achieved an overall accuracy of 95%. Precision and Recall are high across all classes, with weaver ants and ghost ants having the highest precision 98% while fire ants, ghost ants and little black ants have the same recall value 96%. The f1-score is consistently high, indicating balanced performance across precision and recall. The base model demonstrates robust performance, with minimal variation across different classes, suggesting a well-generalized model.

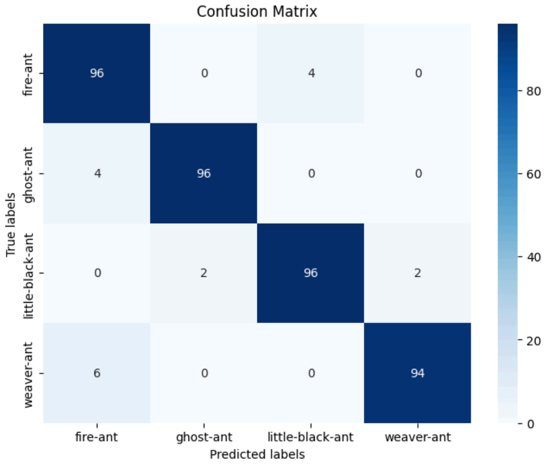

Figure 4: Confusion Matrix for the Base Model

Based on the confusion matrix of the base model, 96 images were correctly classified as fire ants, 96 images were correctly classified as ghost ants, 96 images were correctly classified as little black ants, and 94 images were correctly classified as weaver ants. This shows that the base model performs well on classifying the ant species based on test images.

To assess the robustness of our base model, we compared its performance against three known architectures: DenseNet121, EfficientNetB0, and MobielNetV2. The performance metrics are presented in Tables 2, 3, and 4.

Table 2: Performance Metrics of DenseNet121

DenseNet121		
Set	Accuracy	Loss
Training	98.44%	0.0372
Validation	96.43%	0.1373
Test	94.00%	0.4437

DenseNet121 showed exceptional performance on the training and validation datasets, achieving an accuracy of 98.44% on the training set and 96.43% on the validation set, with very low loss values of 0.0372 and 0.1373, respectively. The test accuracy was 94.00%, with a test loss of 0.4437. This suggests that while DenseNet121 is highly effective during training and validation, its performance on unseen data remains strong but shows a slight decrease compared to its performance on the training and validation sets.

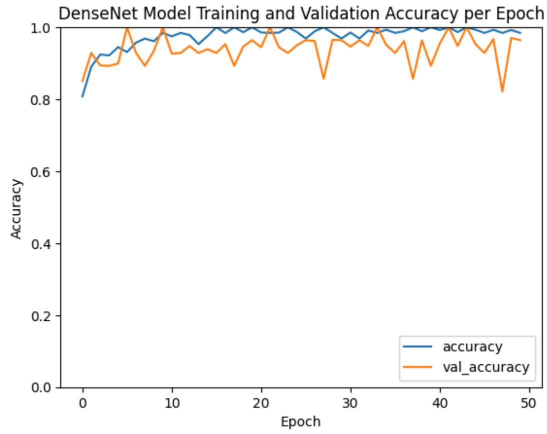

Figure 5: DenseNet121 Model Training and Validation Accuracy Per Epoch

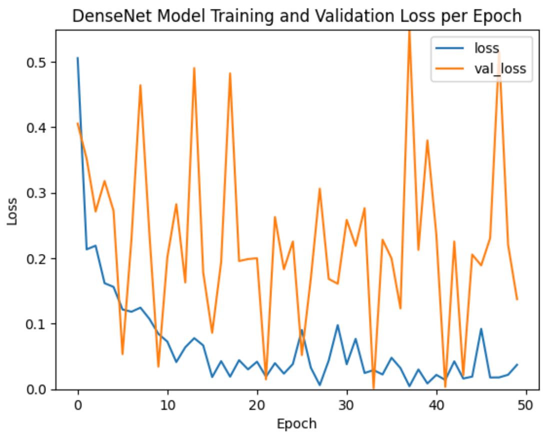

Figure 6: DenseNet121 Model Training and Validation Loss Per Epoch

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DenseNet Model Classification Report:
                  precision    recall  f1-score   support

        fire-ant       0.92      0.97      0.95       100
       ghost-ant       0.94      0.96      0.95       100
little-black-ant       0.92      0.92      0.92       100
      weaver-ant       0.98      0.91      0.94       100

        accuracy                           0.94       400
       macro avg       0.94      0.94      0.94       400
    weighted avg       0.94      0.94      0.94       400
```

Figure 8: Classification Report for the DenseNet121 Model

The classification report for the DenseNet121 Model achieved an overall accuracy of 94%. Weaver ants and ghost ants achieved high precision, 98% and 94% respectively. Fire ants and ghost ants achieved 97% and 96% recall respectively. The f1-score of the DenseNet121 Model shows balance among classes, with slight variations. While the DenseNet121 model performed slightly well, the base model still performed better compared to this model.

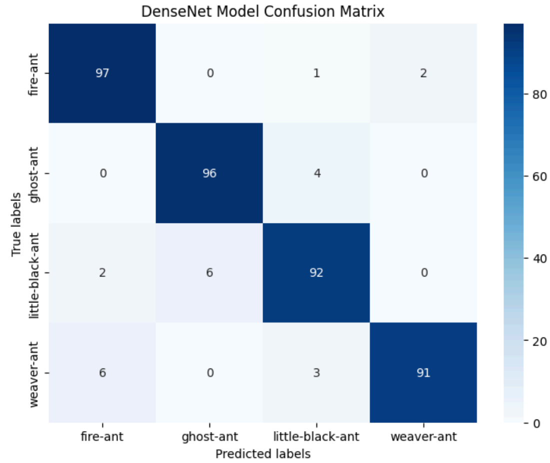


Figure 9: Confusion Matrix for the DenseNet121 Model

Based on the confusion matrix of the DenseNet121 Model, it shows that 97 images were correctly classified as fire ants, 96 were ghost ants, 92 images were little black ants, and 91 images were correctly classified as weaver ants.

Table 3: Performance Metrics of EfficientNetB0

EfficientNetB0		
Set	Accuracy	Loss
Training	26.56%	1.3718
Validation	32.14%	1.3630
Test	25.00%	1.3883

EfficientNetB0 significantly underperformed compared to the other models, with a training accuracy of 26.56% and validation accuracy of 32.14%. The test accuracy was 25.00%, and the loss values were high across all datasets (1.3718 for training, 1.3630 for validation, and 1.3883 for test). This model struggled to learn effectively from the data.

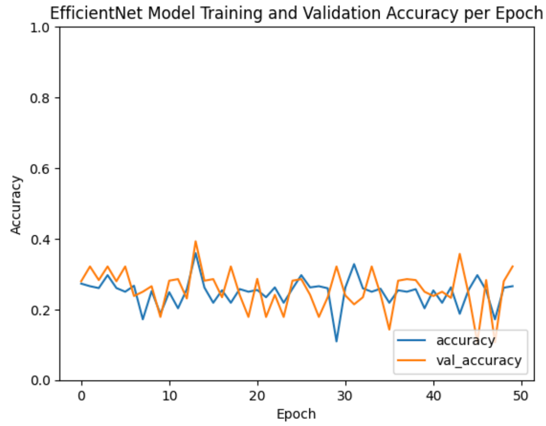


Figure 10: EfficientNetB0 Model Training and Validation Accuracy Per Epoch

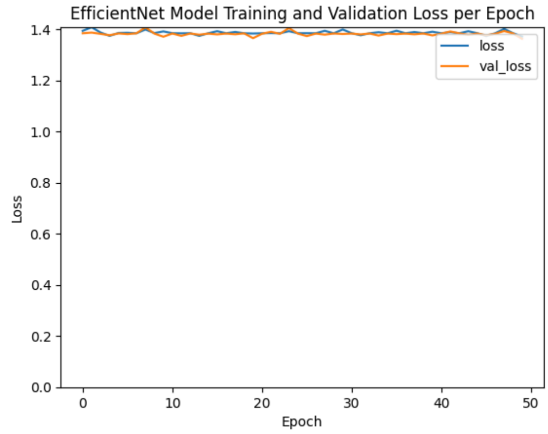
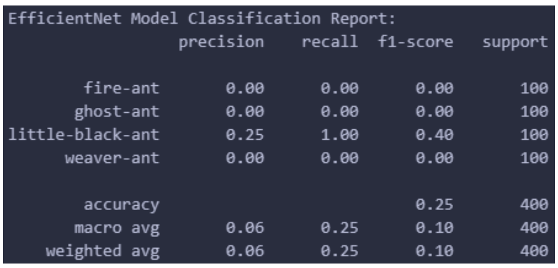


Figure 11: EfficientNetB0 Model Training and Validation Loss Per Epoch



```
EfficientNet Model Classification Report:
                 precision    recall  f1-score   support

       fire-ant       0.00      0.00      0.00       100
      ghost-ant       0.00      0.00      0.00       100
little-black-ant      0.25      1.00      0.40       100
     weaver-ant       0.00      0.00      0.00       100

       accuracy                           0.25       400
      macro avg       0.06      0.25      0.10       400
   weighted avg       0.06      0.25      0.10       400
```

Figure 12: Classification Report for the EfficientNetB0 Model

The classification report for the EfficientNetB0 Model achieved an overall accuracy of 25%, which is extremely low. The precision is low for all classes. Little black ants achieved perfect recall but zero for other classes. The f1-score is very low for all classes. EfficientNetB0 significantly underperformed, only correctly identifying little black ants with high recall but failing to classify the other species correctly, resulting in extremely low precision and f1-scores for those classes.

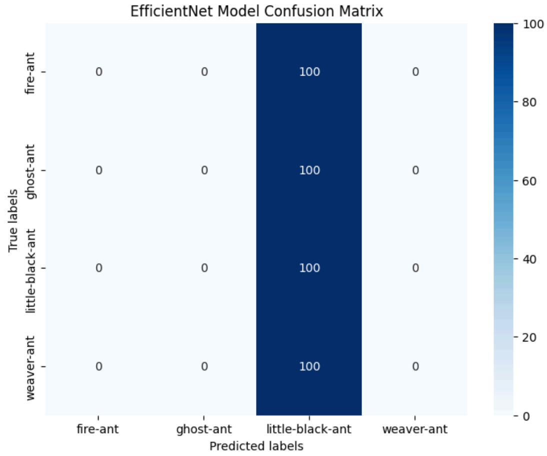


Figure 13: Confusion Matrix for the EfficientNetB0 Model

The confusion matrix for the EfficientNetB0 model showed that the model did not perform well on correctly classifying the images. It can be seen that all images were predicted to be little black ants.

Table 4: Performance Metrics of MobileNetV2

MobileNetV2		
Set	Accuracy	Loss
Training	100%	0.0013
Validation	89.29	0.6765
Test	93.25%	0.4951

MobileNetV2 also performed very well, achieving perfect accuracy on the training and validation datasets 100% with minimal loss (0.0013 for training and 0.6765 for validation). Its test accuracy was 93.25%, slightly lower than the base model and DenseNet121

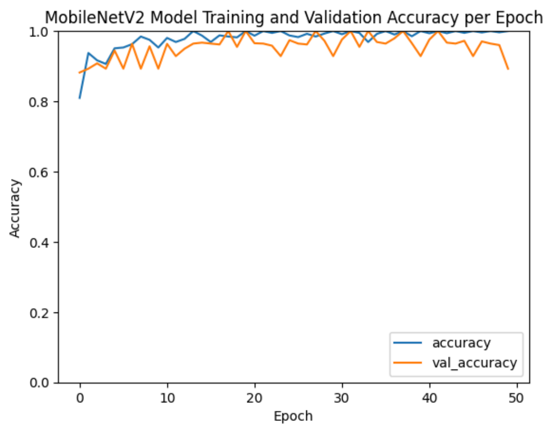


Figure 14: MobileNetV2 Model Training and Validation Accuracy Per Epoch

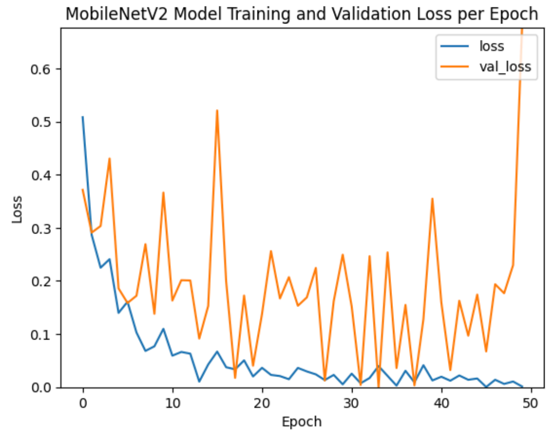


Figure 15: MobileNetV2 Model Training and Validation Loss Per Epoch

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MobileNetV2 Model Classification Report:
                 precision    recall  f1-score   support

       fire-ant       0.88      0.96      0.92       100
      ghost-ant       0.98      0.96      0.97       100
little-black-ant       0.98      0.89      0.93       100
     weaver-ant       0.90      0.92      0.91       100

       accuracy                           0.93       400
      macro avg       0.94      0.93      0.93       400
   weighted avg       0.94      0.93      0.93       400
```

Figure 16: Classification Report for the MobileNetV2 Model

The classification report for the MobileNetV2 Model achieved an overall accuracy of 93%. It achieved high precision across all classes, with little black ants and ghost ants having the highest precision (98%). The highest recall goes to ghost ants and fire ants with both having 96% respectively.

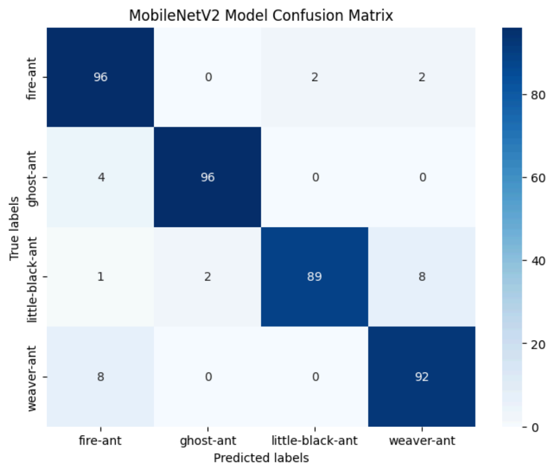

Figure 17: Confusion Matrix for the MobileNetV2 Model

The confusion matrix for the MobileNetV2 Model shows that 96 images were correctly classified as fire ants,96 were correctly classified as ghost ants, 89 were correctly classified as little black ants, and 92 were correctly classified as weaver ants.

Overall, DenseNet121 and MobileNetV2 demonstrated excellent training and validation performance, but DenseNet121 did not outperform the base model in test loss and accuracy. EfficientNetB0's results highlight the challenges it faced during training, making it the least effective model in our comparison. Our base model provided a strong baseline with balanced accuracy and loss across all datasets.

The incorporation of our recommendation system added practical value to our classification model, offering users actionable insights for each ant species identified. This feature enhances the practical utility of our work, providing not only classification results but also useful management advice.

For deploying our model, we opted for deploying it using Streamlit, a popular framework for creating web applications in Python. Streamlit provides an intuitive interface for users to interact with our model, upload images, and receive classification results along with recommendations.

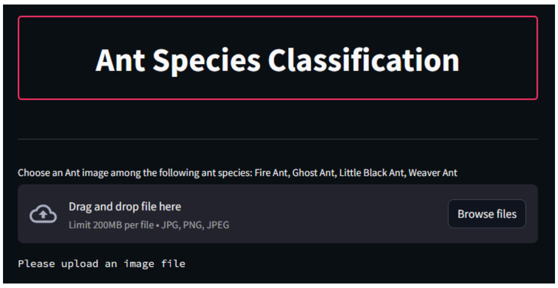

Figure 18: Application GUI

Table 5: Results for the deployed model

5 Images per ant species		
Species	**No. of Correct Classification**	**No. of False Classification**
Fire Ants	5	0
Ghost Ants	5	0
Little Black Ants	5	0
Weaver Ants	4	1
Total	19	1

After testing 20 images of different ant species, the results showed that 19 out of 20 images were correctly classified. This means that the base model that was deployed using Streamlit generalizes well on new data.

IV. CONCLUSION

After extensive experimentation and analysis, our research demonstrates that deep learning and computer vision significantly improve the accuracy and efficiency of ant species identification. Our base model achieved 95.50% test accuracy, indicating great performance in classifying the ant species. Furthermore, comparing our base model to CNN models like DenseNet121 and MobileNetV2, we achieved high test accuracies, with DenseNet121 reaching 94% and MobileNetV2 at 93.25%. The results of the base model outperformed the CNN models we compared it to. Data augmentation enhanced the models' generalization capabilities, and the integration of a recommendation system provided practical management insights for each species identified. Deploying the model via Streamlit ensured user-friendly access, making this system a valuable tool for biodiversity management and scientific research. This study highlights the potential of combining advanced technologies for effective species recognition and management.

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