Enhancing Sustainability of Invasive Species Management using Efficient Deep Learning Paradigms for Preserving Ecosystems Deploying Smart Invasive Species Detection.

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Abstract*— *Invasive species monitoring is vital for ecosystem protection by preventing harmful species from spreading. This study uses a Kaggle dataset to develop deep learning models for detecting invasive species. The model combines cross-validation and data augmentation to improve performance. We first created Convolutional Neural Network (CNN) models with 3-layer and 4-layer structures, achieving accuracies of 89% and 93%, respectively. Then, we applied transfer learning with MobileNet models using different epochs and batch sizes. The best performance (98.1% accuracy) came from MobileNet with 20 epochs and batch size 16. Deeper configurations, such as MobileNet with 40 epochs and batch size 32, showed lower accuracy (87.2%). This approach demonstrates the effectiveness of lightweight models and transfer learning in achieving a balance between accuracy and efficiency for invasive species detection.

1 Introduction

Invasive plant species have several negative ecological impacts; they often compete for the same nutrients as native species and can also be toxic to local fauna. Invasive species cost an estimated 33 billion dollars per year and are "the second-greatest threat" to endangered wildlife after habitat destruction [4]. We chose to examine this problem because of its ecological and cross-industry impact, as well as its reliance on a limited training dataset.

The ability to use smaller datasets to train a neural network is particularly valuable in situations where examples of the intended input are scarce or data collection is costly. By augmenting a training dataset in a targeted way, computer scientists can reduce the required time and cost to create tools for environmental scientists. Furthermore, data augmentation by adding noise can often have the effect of creating a model that is more robust to variations in orientation, lighting, and occlusion [5].

To ensure that the model is not overly specific to particular cases and to generalize effectively across various scenarios, we employed cross-validation techniques. These methods systematically divide the dataset into training and validation splits, allowing the model to learn from diverse subsets of the data while evaluating performance on unseen samples. This approach is especially critical when working with small datasets, as it helps mitigate the risk of overfitting to specific instances[7].

The input of our predictive model is a 3-channel color image of plants on forest floors. Our primary models use transfer learning based on two Convolutional Neural Network architectures: VGG-16 and MobileNet. By leveraging cross-validation and targeted data augmentation, we strive to build models capable of yielding reliable probabilities that the foliage in the provided image contains hydrangea. This approach offers an efficient and scalable solution for invasive species monitoring, with broader applicability in ecological research[10].

[1].

[1] https://huggingface.co/spaces/MohamedZakaria170/invasive-species-detection

2 Sustainable Invasive Species Control via Machine Learning

Invasive species are a significant threat to biodiversity and ecosystem stability, disrupting habitats, outcompeting native species, and causing extinctions. These species also impose substantial economic costs, particularly in agriculture and forestry, amounting to billions annually. Monitoring and management are essential to mitigate these impacts, but traditional methods, including manual surveys and expert identification, are time-consuming and resource-intensive. Machine learning (ML) offers a transformative approach, automating species identification and enabling accurate, real-time monitoring, thus improving the efficiency and scalability of invasive species management efforts [14].

Deep learning models, especially convolutional neural networks (CNNs), have demonstrated high accuracy in classifying species from images. These models process large datasets from remote sensing or on-the-ground image captures with minimal human intervention, enabling faster responses to ecosystems at risk [2].

ML models are also highly scalable. Once trained, they can be applied to different regions or species with minimal cost and effort, allowing for widespread implementation of invasive species monitoring systems. This adaptability supports the development of global conservation strategies and enhances the sustainability of invasive species management [6].

Moreover, leveraging ML aligns with the United Nations Sustainable Development Goals (SDGs), particularly those related to biodiversity conservation, combating climate change, and fostering sustainable practices. By reducing the resources needed for manual monitoring and increasing the precision of interventions, ML contributes to preserving ecosystems and reducing the ecological damage caused by invasive species [8].

[2].

3 Background and Related Work

The importance of automated plant classification has driven extensive research in this area. Traditional methods relied on computer vision techniques to extract features like shape, color, and texture. However, with advancements in convolutional neural networks (CNNs), deep learning approaches have transformed this domain by enabling models to autonomously learn relevant features, significantly enhancing classification accuracy and generalizability [12].

CNNs, on the other hand, have shown potential to overcome these limitations, provided sufficient data and robust data augmentation techniques are employed. Mohanty et al. highlighted that CNN models performed poorly (31.4% accuracy) when tested on images from differing conditions, emphasizing the need for diverse training datasets [15].

Transfer learning has emerged as an effective approach to mitigate data scarcity issues. By fine-tuning pre-trained models like VGG16 and AlexNet, researchers can leverage high-level features from large datasets such as ImageNet, achieving high classification accuracy with smaller datasets [4]. Regularization techniques, data augmentation, and model size optimization can further prevent overfitting and improve generalizability [5, 11].

The detection of invasive species is critical for ecosystem management, yet it poses challenges due to limited datasets and environmental variations. Cross-validation has proven essential for evaluating model robustness. Stratified K-Fold cross-validation has been particularly effective in ensuring balanced performance across subsets. For instance, CNN-based invasive plant detection achieved 92% accuracy using 10-fold cross-validation [13]. Similarly, transfer learning with ResNet50 and InceptionV3, combined with data augmentation, achieved 94% accuracy with 5-fold cross-validation [1]. Hybrid models integrating CNNs and random forests achieved accuracies of 87-91% with 10-fold cross-validation [9].

Despite these advancements, challenges remain, including image variability due to lighting, quality, and plant health. Future research should focus on dynamic data augmentation and multi-modal approaches that incorporate environmental data alongside images to improve model accuracy and robustness [3].

4 The Proposed Model

Invasive species monitoring plays a critical role in safeguarding ecosystems from the destructive impact of non-native species. Using data from the Kaggle competition on invasive species monitoring, this study leverages deep learning techniques to detect and classify invasive plant species. The dataset comprises diverse forest images, categorized into invasive and non-invasive classes. These images serve as the foundation for training and testing advanced machine learning models aimed at automating the classification process.

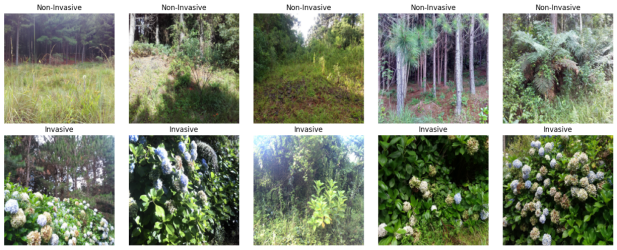
The proposed framework focuses on convolutional neural networks (CNNs), which extract and refine key patterns across multiple layers to enhance classification accuracy. The methodology benefits from trans-

[2] https://github.com/mohamed-zakariya/Invasive_Species

fer learning, utilizing pretrained models to accelerate training and improve performance, especially given the constraints of a limited dataset. By incorporating data augmentation strategies, such as rotations, flips, and brightness adjustments, the dataset's variability is artificially increased, bolstering the model's generalization capabilities.

4.1 Dataset

In this study, we utilized a dataset to classify images into two categories: invasive species and non-invasive species. The images for this task were sourced from **Invasive Species Monitoring Kaggle competition**[3]. . Each image is labeled based on whether the species shown is invasive or non-invasive. The dataset is intended to help develop a model capable of distinguishing between these two categories of species based on image features.



4.2 Corruption in the Test Set

During the process of preparing the data, we encountered a significant challenge with the test set. Some of the images in the test set were found to be corrupted or lacked proper labels, making them unsuitable for direct use in model evaluation. This issue arose from the nature of the dataset provided in the competition, where certain images did not conform to the expected format or were missing metadata necessary for accurate classification.

As a result, we were unable to use these corrupted images for testing purposes. This issue posed a challenge because it meant that a portion of the originally intended test set could not be leveraged for model validation. Without labeled data, it became impossible to evaluate the model's performance on these images, which could potentially introduce bias or reduce the robustness of the model's evaluation.

4.3 Handling the Corrupted Test Set

To address this issue, we decided to exclude the corrupted test set images from the evaluation phase. In place of these, we performed a custom split of the dataset, dividing the available images into new training and test sets. The new split consisted of 80% of the images allocated for training, with the remaining 20% used for testing. This allowed us to continue developing and evaluating the model while avoiding the corrupted data.

Additionally, we ensured that the new test set maintained a balanced representation of invasive and non-invasive species, which is crucial for the performance of the model. By stratifying the split based on the species label, we aimed to avoid any class imbalance that could affect the model's ability to generalize.

- Training Set: The training set contains 80% of the images, with a balanced number of invasive and non-invasive species.
- Test Set: The test set contains the remaining 20% of the images, also with a balanced distribution of invasive and non-invasive species.

The following chart shows the distribution of invasive and non-invasive species in both the training and test sets:

4.4 Data Preprocessing

The dataset used for this study underwent preprocessing by the original creators, which included the removal of duplicate images and adjustments to focus on the relevant regions of the images. Following the initial data cleaning, the dataset was split into three subsets: 80% for training, 10% for validation, and 20% for testing, ensuring a well-distributed set for model evaluation. To enhance the data's utility, Keras' Image Data Generator was employed to perform normalization, rescaling the pixel values of the images from their original range of [0, 255] to a normalized scale of [0, 1]. This normalization step was crucial for optimizing the dataset for use in the convolutional neural network (CNN), facilitating more effective training and faster convergence.

4.5 Data Augmentation

To enhance the model's ability to learn and generalize from the data, data augmentation was applied to the training images. This technique generates new, slightly altered versions of the original images by applying transformations such as rotations, shifts, and flips. The goal of this approach is to artificially increase the number of training examples, helping the model learn from a broader variety of images and improving its performance.

For each image in the training set, multiple augmented versions were created. This significantly expanded the number of images available for training,

[3] `https://www.kaggle.com/competitions/invasive-species-monitoring/data`

providing the model with a richer set of data to learn from. As a result, the size of the training dataset grew substantially after augmentation.

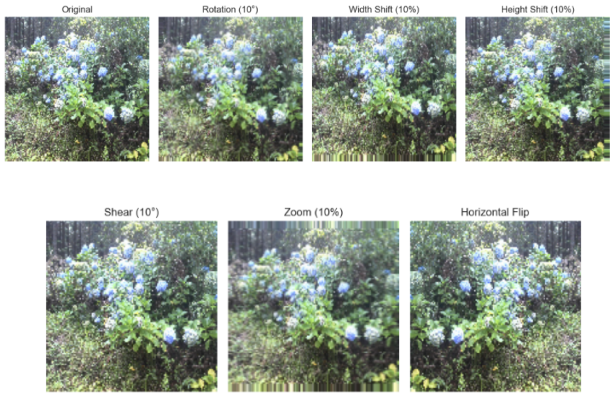


Figure 1: Data Augmentation Representation

4.6 Impact of Data Augmentation on Dataset Size

By applying data augmentation, the number of images in the training set increased considerably. Initially, the training set contained a set number of images. After applying augmentation, the number of images was multiplied, allowing the model to learn from a larger and more varied collection of images. This increase in data size is beneficial because it helps the model become more robust and better equipped to handle unseen examples.

4.7 CNN Models

4.7.1 Overview

We utilized the Invasive Species Monitoring dataset, which comprises labeled images of various species for binary classification to identify invasive species. To ensure compatibility with the CNN architectures, all images were resized to 224×224 pixels, aligning with the input requirements of the models, and pixel values were normalized for optimal training performance.

we applied CNN architectures with two configurations: one with 3 layers and another with 4 layers. To ensure a fair comparison, all other hyperparameters were kept constant across both models. These included the number of epochs, learning rate, batch size, optimizer (Adam), loss function (binary crossentropy), and activation functions. The only difference between the two configurations was the number of layers, allowing us to assess how model depth impacts performance.

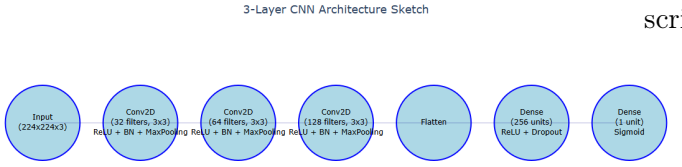


Figure 2: 3 Layers CNN Architecture

4.7.2 3-Layer CNN Architecture

The 3-layer CNN model was designed to perform binary classification for identifying invasive species. The architecture is as follows:

- Input Layer: The model accepts images resized to 224×224×3, where 3 represents the RGB color channels.
- Layer 1: A convolutional layer with 32 filters, each having a 3×3 kernel, followed by a ReLU activation function. Batch Normalization (BN) is applied to stabilize and accelerate training. This layer is followed by a MaxPooling layer with a pool size of 2×2 to reduce spatial dimensions.
- Layer 2: A convolutional layer with 64 filters and a 3×3 kernel, followed by ReLU activation, Batch Normalization, and MaxPooling (2×2).
- Layer 3: A convolutional layer with 128 filters and a 3×3 kernel, ReLU activation, Batch Normalization, and MaxPooling (2×2).
- Flatten Layer: The 3D feature maps produced by the final convolutional layer are flattened into a 1D feature vector.
- Fully Connected Layers: A Dense layer with 256 units and ReLU activation, followed by a Dropout layer (rate = 0.5) to reduce overfitting. An output Dense layer with 1 unit and Sigmoid activation for binary classification.

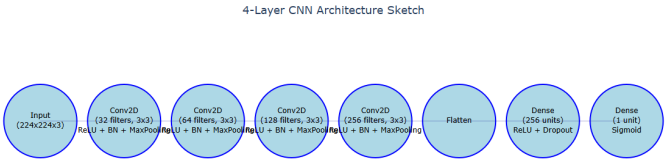


Figure 3: 4 Layers CNN Architecture

4.7.3 4-Layer CNN Architecture

The 4-layer CNN model was an extension of the 3-layer architecture, incorporating an additional convolutional layer to explore how increasing the model's depth impacts performance. The architecture is described below:

- Input Layer: The model accepts input images resized to 224×224×3, representing the width, height, and RGB color channels.

- Layer 1: A convolutional layer with 32 filters, each with a 3×3 kernel, followed by ReLU activation. Batch Normalization (BN) is applied to normalize activations, and MaxPooling (2×2) is used for spatial downsampling.
- Layer 2: A convolutional layer with 64 filters (3×3 kernel) and ReLU activation, followed by Batch Normalization and MaxPooling (2×2).
- Layer 3: A convolutional layer with 128 filters (3×3 kernel) and ReLU activation, with Batch Normalization and MaxPooling (2×2) applied as well.
- Layer 4 (New): An additional convolutional layer with 256 filters (3×3 kernel), ReLU activation, Batch Normalization, and MaxPooling (2×2). This layer increases the network's depth and capacity to capture more complex features.
- Flatten Layer: The multidimensional feature maps generated by the convolutional layers are flattened into a 1D feature vector.
- Fully Connected Layers:

  A Dense layer with 256 units and ReLU activation, followed by a Dropout layer (rate = 0.5) to reduce overfitting. An output Dense layer with 1 unit and Sigmoid activation for binary classification.

4.8 TRANSFER LEARNING

4.8.1 Overview

Transfer learning is a technique where a pre-trained model is adapted for a new but related task. It was chosen for this study due to its efficiency in leveraging pre-learned features from large datasets (like ImageNet) and applying them to the task of invasive species classification. This approach reduces computational requirements and training time while improving model accuracy on relatively small datasets.

4.8.2 Transfer Learning Using MobileNet

MobileNet Architecture MobileNet, a lightweight and efficient convolutional neural network, was selected for its optimized performance on resource-constrained devices.

- Pre-trained Weights: The base model used weights trained on the ImageNet dataset. These weights provide robust feature extraction for general image recognition tasks, making them suitable for transfer to the invasive species dataset.
- Customization for Invasive Species Classification: The first 30 layers of the MobileNet model were frozen to retain learned low-level features like edges and textures, which are common across tasks.
  - A custom classification head was added:
  - A Flatten layer to transform feature maps into a 1D vector.
  - A fully connected Dense layer with 256 units and ReLU activation for learning task-specific patterns.
  - A Dropout layer with a rate of 0.5 to mitigate overfitting.
  - A final output layer with a sigmoid activation for binary classification (invasive or non-invasive species).
- Implementation Details

  The hyperparameters were carefully selected to optimize the performance of the model for the task of invasive species classification. A learning rate of 10^{-4} was chosen, balancing efficient convergence and the prevention of overshooting during optimization. The Adam optimizer was utilized due to its capability to handle sparse gradients and adaptively adjust learning rates, making it highly effective for training deep neural networks. The loss function selected was binary cross-entropy, which is ideal for binary classification tasks like distinguishing between invasive and non-invasive species. Model performance was evaluated using accuracy as the primary metric, providing a clear measure of the model's ability to correctly classify the images. The implementation was carried out using TensorFlow and Keras, frameworks that offer robust support for transfer learning and model customization, facilitating efficient adaptation of the MobileNet architecture to the specific requirements of the dataset.

5 Result

5.1 Validation-Training Plots

To evaluate the performance of the two CNN architectures (3-layer and 4-layer) for emotion recognition, we present the validation-training accuracy and loss plots for the best-performing folds of each model.

5.1.1 4-Layer CNN Architecture (Fold 4)

The training accuracy remains consistently high across epochs, indicating that the model fits the

training data well. However, the validation accuracy shows fluctuations, suggesting potential overfitting or variability in how well the model generalizes to unseen data. Despite this, the validation accuracy still reaches high values in several epochs, demonstrating that the 4-layer architecture is effective in capturing the underlying patterns of the data.
The loss plot reflects a stable and low training loss, while the validation loss occasionally spikes, which aligns with the fluctuating validation accuracy. This behavior may indicate sensitivity to certain data points in the validation set.

5.1.2 3-Layer CNN Architecture (Fold 1)

The training accuracy steadily improves over epochs, reaching high levels, and the validation accuracy shows a clear upward trend with less variability compared to the 4-layer model. This suggests that the 3-layer architecture is less prone to overfitting and maintains better consistency in generalization.
The loss plot reveals a significant reduction in both training and validation loss over epochs, indicating effective learning and better optimization of the model parameters.

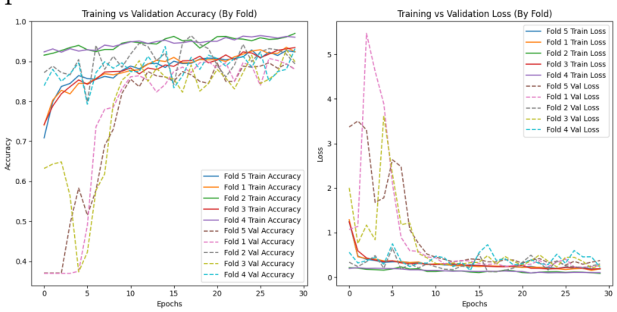


Figure 4: Train-validation on CNN of 3 layers

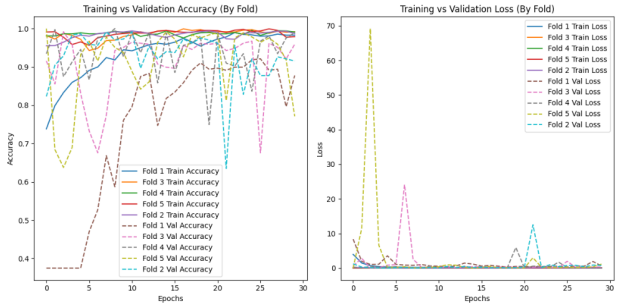


Figure 5: Train-validation on CNN of 4 layers

These differences highlight the trade-offs between the two architectures. While the 4-layer model may capture more complex features, it also exhibits more variability in validation performance, whereas the 3-layer model demonstrates more stable generalization.

5.1.3 Confusion Matrix for both 3-layers and 4-layers of CNN

Confusion Matrix Analysis for 3-Layer CNN In the 3-layer CNN model, Fold 1 showed strong predictive performance, as demonstrated by the confusion matrix. Among the 459 samples, the model correctly identified 138 out of 169 instances as "Not Invasive," yielding a recall of 0.82 for this class. However, 31 samples were misclassified as "Invasive." For the "Invasive" class, the model achieved higher accuracy, correctly classifying 269 out of 290 samples, with only 21 instances misclassified. The precision and recall for the "Invasive" class were both higher than those for the "Not Invasive" class, leading to an overall accuracy of 0.89. The macro-average F1-score was 0.88, showing balanced performance across both classes.
Confusion Matrix Analysis for 4-Layer CNN For the 4-layer CNN, Fold 4 yielded the best results, with significantly improved classification accuracy. Out of 169 samples labeled as "Not Invasive," the model correctly identified 146, achieving a recall of 0.86 for this class. Only 23 samples were misclassified as "Invasive." In the "Invasive" class, the model showed even greater precision and recall, correctly classifying 281 out of 290 samples and misclassifying only 9. This resulted in a class recall of 0.96 for "Invasive." The overall accuracy was 0.93, and the macro-average F1-score was 0.92, demonstrating excellent overall performance. The 4-layer CNN shows a clear improvement in both precision and recall for both classes compared to the 3-layer CNN.

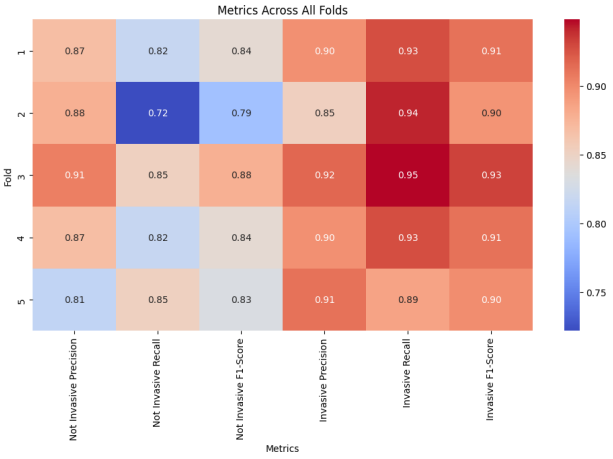


Figure 6: Metrics Across All folds in 3-layers in CNN

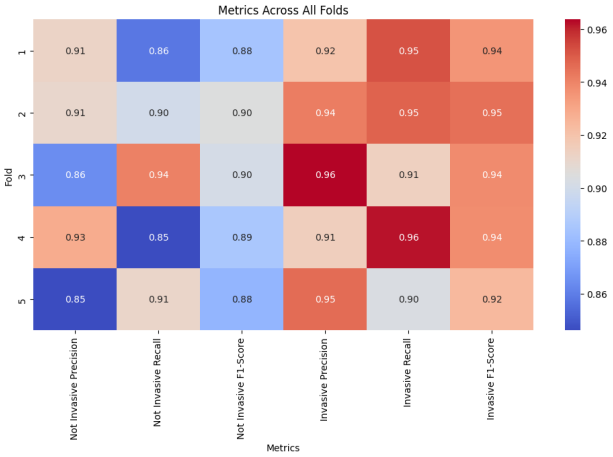


Figure 7: Metrics Across All folds in 4-layers in CNN

We can see through the figures that the deep network has a more accurate result than the shallow network's, as most of the cells in the primary diagonal (number of correct recognitions) have higher values , and most of the cells not in the primary diagonal (number of incorrect recognitions) have lower values. Moreover, we can also know which labels are easily to be incorrect recognized, and be confused with other labels. For example, in the shallow network, the Anger, Fear and Neutral often be recognized as label Sad. The label Disgust have a small amount of data, so the accuracy is quite low and not stable.
In addition, we computed the table of accuracy (the percentage of correctly recognitions case of each label).

5.2 Transfer Learning

5.2.1 MobileNet

- Model Architecture:

  For this study, MobileNet was selected as the base model for transfer learning due to its lightweight nature and efficiency, which make it well-suited for applications involving large-scale image classification tasks on limited computational resources. MobileNet's architecture leverages depthwise separable convolutions, significantly reducing the number of parameters while maintaining high accuracy. This allows the model to achieve a balance between computational efficiency and performance, which is particularly important given the diverse nature of the dataset.

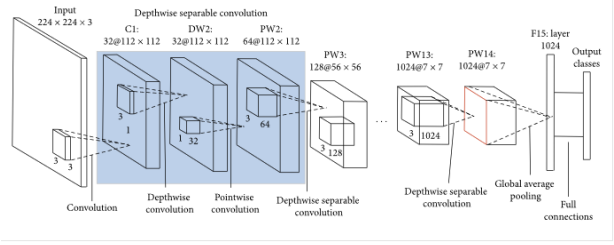


Figure 8: MobileNet Architecture

- The validation performance: for all configurations was evaluated using 5-fold cross-validation. For each combination of epochs and batch size, the validation accuracy across all folds was recorded, and the average was used to identify the best-performing model. Below is a summary of the validation accuracies:

Table 1: Validation Accuracy Across Configurations

Eps,Bat	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5
20,16	96.2%	94.6%	96.5%	97.3%	95.1%
20,32	97%	95.4%	97.3%	96.5%	96.2%
30,32	96%	95.6%	96.7%	97.8%	93.7%
40,32	89.1%	86.1%	63.2%	85%	62.9%

- firstly MobileNet with 20 Epochs and 16 Batchs: Validation Curves for each fold:
Confussion Matrix: The results of the 5-fold cross-validation indicate that folds 1 and 5 achieved the highest performance, with both folds yielding identical outcomes in terms of percentage accuracy. These consistent results suggest that the model's performance is stable and reliable across different subsets of the data, particularly in these two folds

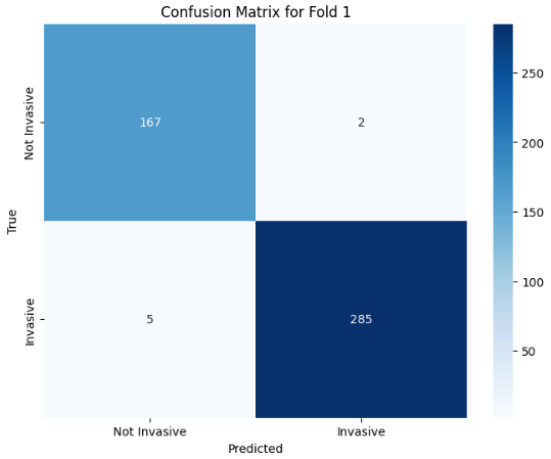


Figure 9: Validation Confusion Matrix of 20 epochs and 16 Batchs of fold 1

Metrix Accross all Folds: the outcomes shows that The total average accuracy for this heatmap is approximately 97.5%.

Figure 10: Matrics Acrros All folds according 20 Epochs and 16 Batchs

- firstly MobileNet with 20 Epochs and 32 Batchs: Validation Curves for each fold:

1 0.9

Figure 11: Validation Acc&Loss with 20 epochs and 32 Batchs

Confussion Matrix: The results of the 5-fold cross-validation indicate that folds 1 and 5 achieved the highest performance, with both folds yielding identical outcomes in terms of percentage accuracy. These consistent results suggest that the model's performance is stable and reliable across different subsets of the data, particularly in these two folds

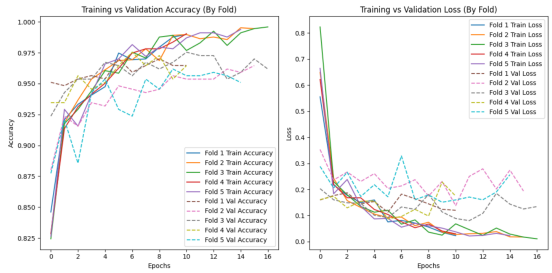


Figure 12: Validation Confusion Matrix of 20 epochs and 32 Batchs of fold 1

Metrix Accross all Folds: the outcomes shows that The total average accuracy for this heatmap is approximately 98.1%.

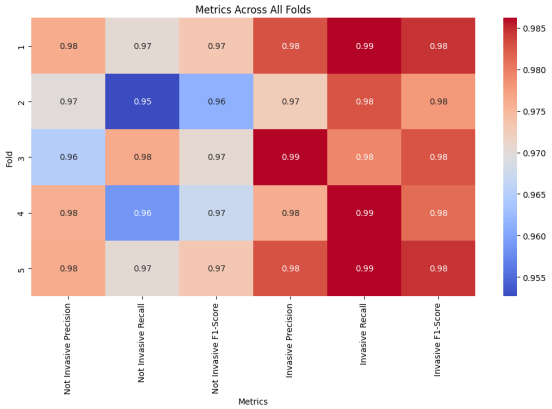


Figure 13: Metrics of MobileNet with 20 epochs and 32 Batchs

- firstly MobileNet with 30 Epochs and 32 Batchs: Validation Curves for each fold:

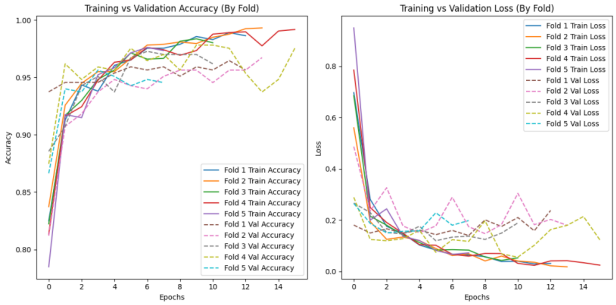


Figure 14: Validation Acc&Loss with 30 epochs and 32 Batchs

Confussion Matrix: The results of the 5-fold cross-validation indicate that folds 1 and 5 achieved the highest performance, with both folds yielding identical outcomes in terms of percentage accuracy. These consistent results suggest that the model's performance is stable and reliable across different subsets of the data, particularly in these two folds

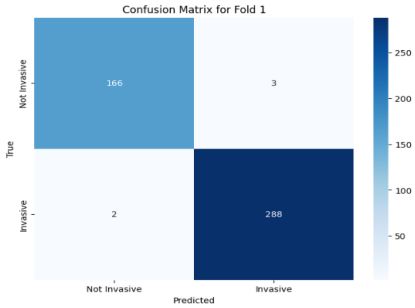


Figure 15: Validation Confusion Matrix of 30 epochs and 32 Batchs of fold 1

Metrix Accross all Folds: the outcomes shows that The total average accuracy for this heatmap is approximately 97.5%.

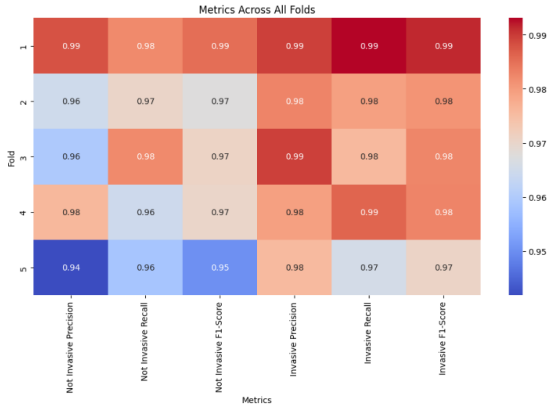


Figure 16: Metrics of MobileNet with 40 epochs and 32 Batchs

- firstly MobileNet with 40 Epochs and 32 Batchs: Validation Curves for each fold:

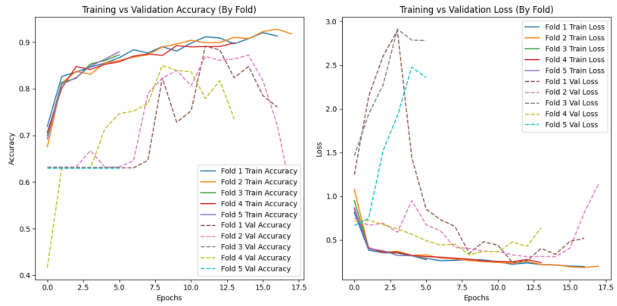


Figure 17: Validation Acc&Loss with 40 epochs and 32 Batchs

Confussion Matrix: The results of the 5-fold cross-validation indicate that folds 1 and 5 achieved the highest performance, with both folds yielding identical outcomes in terms of percentage accuracy. These consistent results suggest that the model's performance is stable and reliable across different subsets of the data, particularly in these two folds

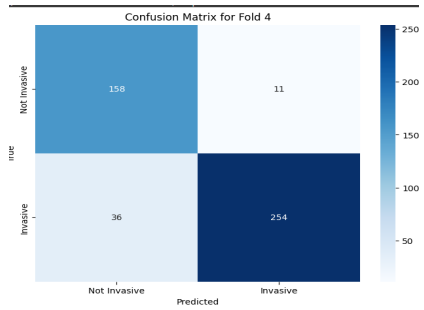


Figure 18: Validation Confusion Matrix of 40 epochs and 32 Batchs of fold 4

Metrix Accross all Folds: the outcomes shows that The total average accuracy for this heatmap is approximately 98.1%.

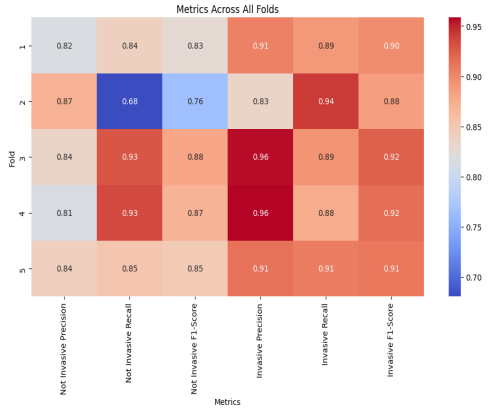


Figure 19: Metrics of MobileNet with 40 epochs and 32 Batchs

Table 2: Results of the experiment

Model Architecture	Test Accuracy
CNN-3 layers	89%
CNN-4 layers	93%
MobileNet (20,16)	98.1%
MobileNet (20,32)	97.5%
MobileNet (30,32)	97.4%
MobileNet (40,32)	87.2%

6 Conclusion

This study successfully demonstrated the effectiveness of convolutional neural networks (CNNs) and transfer learning techniques for invasive species monitoring using image data. The results highlight the superior performance of transfer learning, particularly using MobileNet, over traditional CNN architectures. MobileNet achieved the highest accuracy of 98.1

Data augmentation and cross-validation were instrumental in enhancing model robustness and generalization, addressing challenges such as limited dataset size and environmental variability. The systematic comparison of 3-layer and 4-layer CNNs also underscored the importance of balancing model complexity and generalization capacity.

By automating the invasive species identification process, the proposed approach offers a cost-effective and scalable solution for biodiversity conservation and environmental management. Future work can explore integrating multi-modal data and dynamic augmentation techniques to further improve accuracy and applicability across diverse ecological scenarios.

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