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RESEARCH ARTICLE

A SIMPLE ENSEMBLE METHOD FOR TRANSFER LEARNING-BASED COTTON LEAF DISEASE DETECTION USING MACHINE LEARNING

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ABSTRACT

The agricultural sector in South Asia, especially countries like Bangladesh, China, and India, relies heavily on cotton, a crop vital to both the economy and the global textile industry. However, cotton production faces significant challenges from leaf diseases, which can drastically reduce crop yield, impacting farmers' livelihoods and the region's economy. Traditional methods for detecting these diseases involve manual inspection, which is labor-intensive, time-consuming, and prone to error. Although machine learning and deep learning approaches have been developed for automated disease detection, most existing models require large datasets and high computational resources, limiting their applicability in resource-constrained areas. This paper presents a novel, lightweight ensemble model optimized for detecting cot- ton leaf diseases on mobile devices using a small dataset. Leveraging transfer learn- ing, our approach enables farmers to use as few as 40 known images to fine-tune the ensemble model directly on their devices, achieving high classification accuracy even with minimal data. We evaluate four pre-trained models—ResNet50, MobileNetV2, EfficientNetB0, and InceptionV3—and compare their effectiveness. After trans- fer learning, ResNet50 achieved the highest accuracy of 97.87%, and InceptionV3 achieved 93.61%, demonstrating their suitability for small-scale, mobile-friendly ap- plications. The ensemble model achieved a classification accuracy of 95.7% through averaging and 97.87% using majority voting. This approach empowers farmers in de- veloping regions by providing a practical, adaptable tool for early disease detection, potentially reducing crop loss and enhancing yield with limited resources.

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INTRODUCTION

Agriculture forms the backbone of many economies in South Asia, including countries like Bangladesh, China, and India (Patil and Burkpalli, 2021; Nadiruzzaman et al., 2021. Cotton, often called "white gold," is one of the most economically significant crops in these regions, with a global trade value of 40 billion US dollars, expected to rise to 60 billion US dollars by 2030 (Meyer et al., 2023). In Bangladesh alone, the garment industry, which heavily relies on cotton, generated over 20 billion US dollars in export revenue (Mohiuddin, 2008). However, cotton production is constantly threatened by pests, diseases, and the adverse effects of climate change. For example, cotton leaf diseases alone have reduced production by 25% in India (Khairnar and Goje, 2020), and China has experienced up to 50% losses in certain regions (Chen et al., 2020). To combat this, it is critical to develop effective and accessible solutions for early disease detection. Traditional disease detection methods, which often rely on farmers or specialists manu- ally inspecting plants, are time-consuming, labor-intensive, and prone to errors. Misdia- gnosing diseases with similar symptoms can lead to the overuse or misuse of pesticides, which not only harms crops but also the environment. Although significant advances have been made in automated detection using machine learning (ML) and deep learning (DL) techniques (Saleem et al., 2021; Talukder et al., 2023; Kaur et al., 2018), many of these solutions depend on large datasets and complex models that require substantial compu- tational resources. This creates a gap in applicability for farmers in developing countries who may not have access to such resources. In this paper, we introduce a lightweight ensemble model designed to detect cotton plant diseases with minimal data, optimized for mobile devices. The core idea is to allow farmers to use as few as 40 images of known diseases—images they are confident about—to perform transfer learning on the pre-trained ensemble model. This means that instead of relying on large, predefined datasets, the model can be fine-tuned with a small dataset on the user's mobile device, making it adaptable and efficient. This approach is particularly suitable for farmers in resource-constrained environments where access to high-end computing infrastructure is limited. The ensemble model provides a solution that is both powerful and accessible, offering classification accuracy of around 93% despite the smaller dataset used, a performance comparable to models trained on much larger datasets in previous studies (Mehta et al., 2018; Jenifa et al., 2019). The key innovation of our approach lies in its practicality. While other studies have demonstrated high accuracy with larger datasets, our method is tailored to real-world use cases where data collection may be limited, and computational power is scarce. The lightweight nature of the model, combined with the flexibility of transfer learning, allows farmers to use a mobile application to fine-tune the model on-site. This empowers them to detect new diseases in their crops efficiently, thereby reducing the risk of crop loss and improving yields. By focusing on a small dataset for transfer learning, we ensure the model's relevance for regions where access to large agricultural datasets and advanced technology is not feasible. In Section 1.1, we describe the dataset used for our analysis. In Section 2, we outline the methodology employed in our study. The results of our analysis are presented in

Section 3, followed by a conclusion in Section 4.

Data: The dataset used for this study was curated from publicly available repository in Kaggle (Dhamodharan, 2023). The dataset comprises 200 images across five categories, repres- enting five distinct cotton leaf diseases (Aphids, Army Worm, Bacterial Blight, Powdery Mildew, and Target Spot) and healthy leaves. Each category contains 40 labeled images.

Data Preprocessing

Image Resolution and Scaling: All images were resized to a resolution to pixels to en- sure uniformity across inputs, matching the expected input size of the pre-trained models. The pixel values were normalized to a range of [0, 1] for compatibility with deep learning models.

Data Augmentation: Given the limited size of the dataset, data augmentation tech- niques were employed to artificially increase its diversity and reduce the risk of overfitting (Lecun et al., 2010). The following augmentation techniques were employed:

- **Rotation**: Random rotations up to 30°.
- **Flipping:** Horizontal and vertical flips.
- **Zooming:** Random zoom ranges up to 20%.

Brightness Adjustment: Random changes to image brightness.

Train-Test Split: The dataset was split into 80% training and 20% validation subsets to ensure a balanced evaluation. Stratified sampling was applied to maintain an equal representation of all categories in both subsets. This dataset reflects real-world conditions, incorporating variations in lighting, angles, and environmental conditions. The diversity ensures the model's robustness and its ability to generalize to unseen data effectively.

METHODS

First we explain the transfer learning approach use to adapt pre-trained convolutional neural networks (CNNs) for this task. Then we explain our choice of the deep architectures used in the analysis, followed by fine tuning and hyperparameter optimization.

Transfer Learning: Deep learning models, particularly convolutional neural networks (CNNs), have proven highly effective for image classification tasks by identifying complex patterns within data(Zhao et al., 2024). However, these models require substantial time, computational resources, and large datasets for optimal training, making them impractical in many real- world scenarios, especially for farmers in developing countries who might not have access to vast labeled datasets. This is where transfer learning becomes a valuable technique (Hussain et al., 2018). In transfer learning, a model trained on a source task and source domain is reused to perform a target task in a target domain. The intuition behind this approach is that the model has already learned useful representations (e.g., edges, textures) during its training on the source domain, which can be leveraged when working on the target domain, thus requiring less data and computation. This makes transfer learning particularly powerful when dealing with small datasets, as in our case, where only 40 images per disease are available for training the model. Mathematically, let $D_S = \{X_S, Y_S\}$ represent the source domain with input data X_S and corresponding labels Y_S. The source task T_S consists of a predictive function $f_S(X_S)$ learned from D_S. Similarly, let $D_T = \{X_T , Y_T \}$ represent the target domain, where X_T is the input data and Y_T are the labels for the target task T_T . The goal of transfer learning is to adapt the knowledge from the source task T_S to improve performance on the target task T_T with the target domain D_T, typically under the assumption that $D_S \neq D_T$ and $T_S \neq T_T$. In our project, we utilize transfer learning to fine-tune pre-trained models on a small dataset, allowing us to achieve a respectable accuracy of approximately 93% despite using far fewer images than typically required.

Deep Learning Models: For the purpose of this study, we experimented with four pre-trained models: ResNet50, MobileNet, InceptionV3, and EfficientNetB0. Each model has distinct advantages in terms of accuracy, computational efficiency, and ease of transfer learning, which makes them ideal candidates for developing a lightweight, real-time disease detection system that can be deployed on mobile devices.

ResNet50: ResNet (Residual Network) addresses the problem of vanishing gradients, which often occurs in deep networks, by incorporating skip connec- tions. These connections allow the gradient to bypass certain layers, preventing it from diminishing through the network's depth. The network essentially learns to map residuals (or the difference between the input and output) instead of directly trying to learn complex transformations. ResNet50 is a 50-layer deep architecture and is widely recognized for its superior accuracy on various image classification tasks. The introduction of residual blocks allows deeper networks to converge more effectively and quickly, making it ideal for our use case where training resources are limited (He et al., 2015).

MobileNetV2: MobileNetV2 is a lightweight model designed for mobile and embedded vision applications. It introduces depthwise separable convolutions, which drastically reduce the number of parameters and computational cost without significantly compromising accuracy. This makes MobileNetV2 a suitable model for deployment on mobile devices, ensuring real-time inference without requiring high- end hardware. In our case, it allows farmers to detect diseases in real-time using handheld devices (Sandler et al., 2019).

EfficientNet: EfficientNet employs compound scaling, which systematically balances the depth, width, and input resolution of the network. This scaling method enables EfficientNet models to outperform previous architectures with fewer parameters and FLOPS. A notable aspect of EfficientNet is its use of depthwise separable convolutions, where a standard convolution operation is split into two smaller operations: depthwise and pointwise convolutions. This approach significantly reduces the number of parameters and computations, making the model suitable for resource-constrained environments. EfficientNetB0, the smallest variant, offers an ideal tradeoff between computational efficiency and accuracy, making it well-suited for our application on mobile devices. By using this model, farmers can achieve high disease classification accuracy on handheld devices with limited computational power (Tan and Le, 2020).

InceptionV3: InceptionV3's architecture captures features at multiple scales by using convolutional layers of varying sizes (1x1, 3x3, 5x5) in parallel. This allows the model to extract both

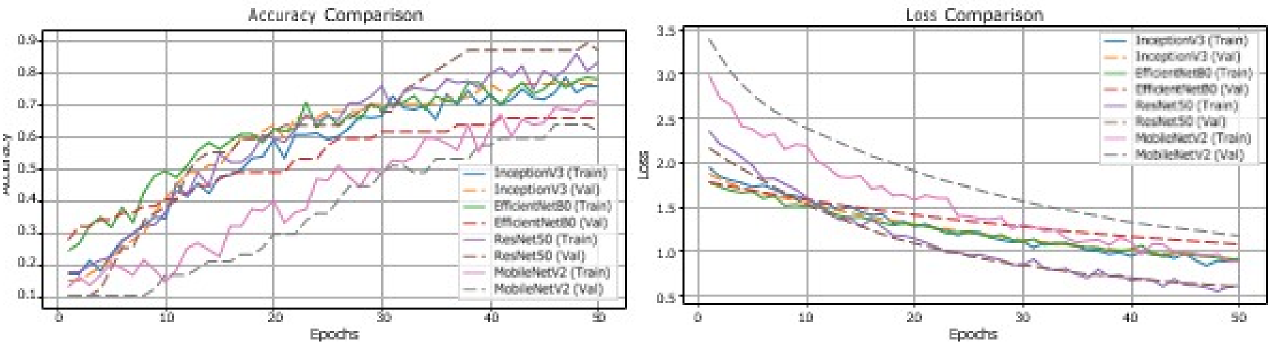

Figure 1. The plot above shows the Accuracy and Loss for various deep learning ar- chitechture as function of epoch.

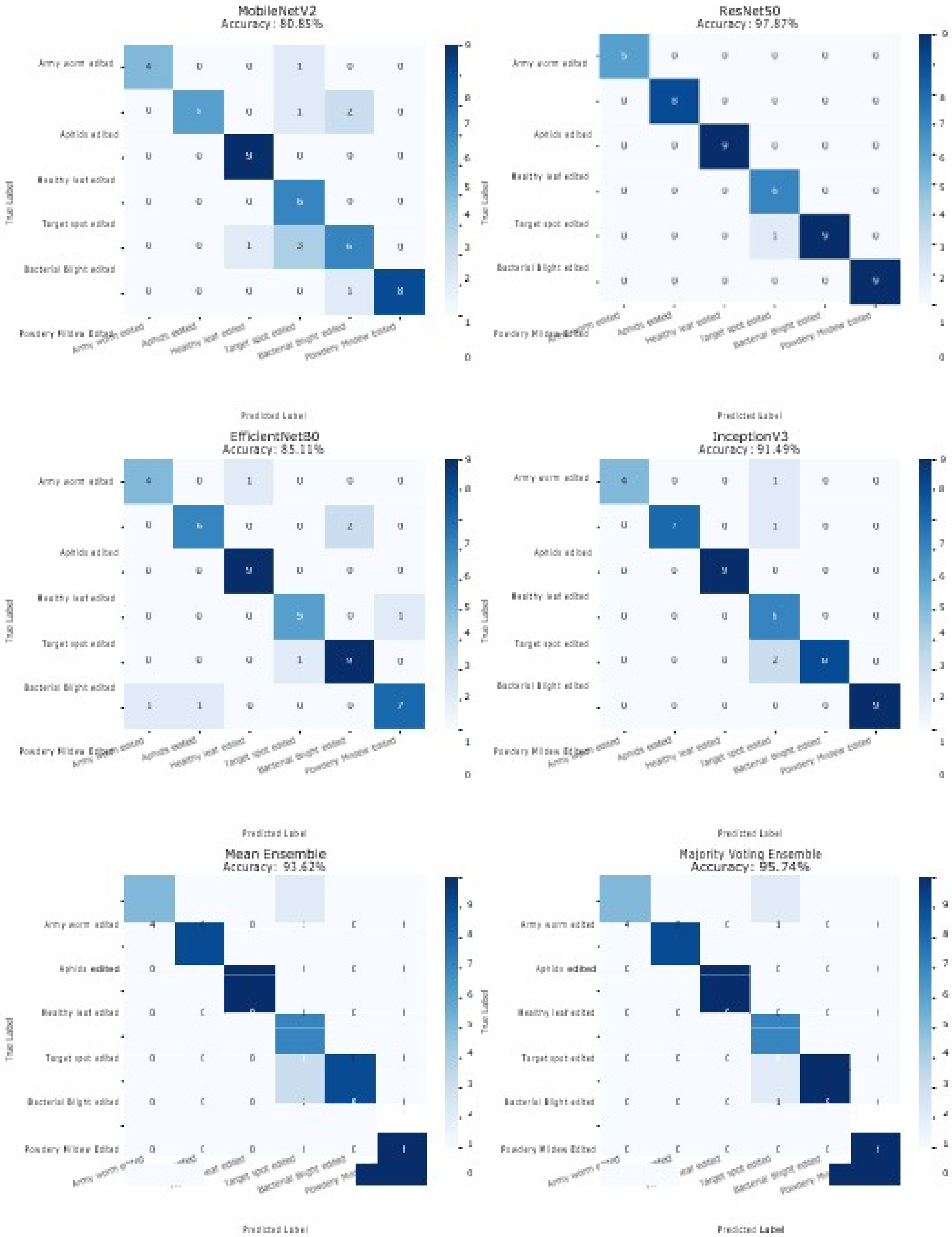

Figure 2. The plot above shows the confusion matrix for all the architechtures along with ensemble models for validation data.

fine and coarse details from images, making it highly effective for image classification tasks involving subtle differences, such as detecting different types of cotton plant diseases. By factorizing larger convolutions into smaller, more efficient operations (e.g., replacing 5x5 convolutions with two consecutive smaller ones), InceptionV3 maintains high performance while redu- cing computational cost. Its multi-scale feature extraction abilities make it ideal for tasks with limited training data, as it can capture diverse patterns within the images, leading to better generalization (Szegedy et al., 2015).

For each model, we performed the following steps:

- **Removal of Classification Head:** We removed the fully connected classification layer (head) from the pre-trained models, which originally classified images into 1000 classes. This is essential since our task involves 6 distinct classes (5 disease classes and a healthy class) of cotton leaf diseases.
- **Custom Classification Layer:** After removing the original head, we added a custom classification head consisting of a fully connected layer followed by a softmax activation function. This configuration allows the model to output the probability distribution across the 6 classes. The softmax function ensures that the sum of probabilities for each class equals 1, providing clear predictions of disease classification.

Training and Fine-Tuning Strategy:

We adopted a two-stage training strategy to leverage the pre-trained knowledge while avoiding overfitting:

- **Training the New Classification Head:** Initially, we froze all the pre-trained layers of each model and trained only the newly added classification head. This approach ensures that the model retains the powerful feature extraction cap- abilities learned from ImageNet while focusing the training effort on learning the specific patterns of the cotton leaf disease dataset. We used a learning rate of 1×10^{-4}, which is suitable for training the new layer while preserving the knowledge from pre-trained layers.
- **Fine-Tuning the Top Layers:** After training the classification head, we un- froze the top 100 layers of each model and fine-tuned them using a smaller learning rate to prevent overfitting. Fine-tuning is a crucial step in transfer learning as it allows the model to adjust its high-level feature representations to better fit the target domain while maintaining its generalized knowledge from the source domain. By using a smaller learning rate in this phase, we minimize the risk of significant changes to the pre-trained weights, allowing for a smoother adaptation to the new task.

Hyperparameters and Optimization:

For all models, we used the Adam optimizer due to its adaptive learning rate properties, which help balance speed and precision in gradient descent. The initial learning rate was set to 1×10^{-4} during the classification head training and reduced further to 1×10^{-5} during the fine-tuning stage (Ge and Yu, 2017). Early stopping was implemented with a patience of 3 epochs to prevent overfitting and reduce unnecessary training time. Crossentropy loss was used as the loss function, as it is well-suited for multi-class classification tasks.

RESULTS

Following the fine-tuning process, each model demonstrated varying levels of performance in accurately classifying cotton plant diseases. MobileNetV2 achieved a validation accuracy of 80.85%, EfficientNetB0 reached 85.11%, InceptionV3 achieved 91.49%, and ResNet50 demonstrated the highest performance with 97.87% accuracy. To further enhance classification reliability, we implemented ensemble techniques, achieving 93.62% accuracy with average prediction (ensemble averaging) and 95.74% accuracy using majority voting. The outstanding performance of ResNet50 and InceptionV3 can be attributed to their specific architectures, which are particularly adept at identifying and learning hierarchical patterns within images. ResNet50, with its deep architecture and skip connections, efficiently mitigates the vanishing gradient issue, allowing the model to retain feature representations effectively as the depth increases. This is particularly beneficial when dealing with complex patterns, as it enables the model to "skip" certain transform- ations, learning residual mappings that contribute to superior performance. Similarly, InceptionV3's architecture excels in capturing spatial information at multiple scales due to its unique inception modules. These modules allow the network to observe fine-grained and large-scale patterns within the same layer, providing comprehensive feature extraction across various scales. This is particularly advantageous for disease classification, where subtle variations in texture and color may be indicators of specific diseases. Figure 1, we plot the accuracy and loss of various deep learning architectures as a function of epochs. The training accuracy increases steadily for all models, but at different rates ResNet50 and InceptionV3 appear to converge to higher accuracies faster. MobileNetV2 shows slower progress, indicating it may require more epochs or better tuning to achieve high accuracy. ResNet50 and InceptionV3 appear to outperform other models in both accuracy and loss, which aligns with their architecture strengths for feature extraction.

CONCLUSION

This study highlights the potential of leveraging transfer learning and lightweight deep learning models for real-time cotton disease classification in resource-constrained environments. By fine- tuning pre-trained models such as ResNet50, MobileNetV2, InceptionV3 and EfficientNetB0 with a small dataset of just 40 images per class, we achieved remarkable accuracy levels, with ResNet50 achieving 97.87% and the ensemble majority voting approach matching this performance. The mobile-friendly design of our approach empowers farmers in developing regions to detect diseases effectively and take timely action, reducing crop losses and enhancing productivity. This innovative solution addresses the challenges of limited data and computational resources, providing a practical tool that aligns with real-world constraints. Future work could explore expanding the dataset, integrating additional disease categories, and further optimizing the model for even lower-resource environments.

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Data Availability Statement: *The data underlying this article are available in* Cotton plant disease dataset, at https://www.kaggle. com/ datasets/dhamur/cotton-plant-disease.

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