Developing a system for Leaf Disease Detection

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Abstract

The main objective of this project is proposing a system for detecting leaf diseases using different deep learning models. The system utilizes deep learning models to classify images of leaves into healthy or diseased categories and identify their diseases. To improve the accuracy, precision, and recall of the system, you have employed the concepts of knowledge distillation and ensemble learning. Knowledge distillation involves transferring the knowledge of a large, accurate model to a smaller model, allowing the smaller model to learn from the large model's predictions. This approach can improve the accuracy of the smaller model while reducing the computational resources required. Ensemble learning involves combining multiple models' predictions to obtain a more accurate prediction. This approach can improve the system's overall accuracy, precision, and recall by taking advantage of each model's strengths and weaknesses. Your system includes an interface that allows users to select different models to detect leaf diseases. The results demonstrate that the ensembled model achieves comparable accuracy, precision, and recall to the larger teacher model while requiring less computational resources and time. Github Link: https://github.com/Shilajit77/Leaf2

1. Introduction

With the growing demand for food production, the need for efficient and reliable plant disease detection methods is more pressing than ever before. Deep learning models have shown promise in detecting leaf diseases in plants, as they can analyze large amounts of data, learn patterns, and classify images into different categories, including healthy and diseased leaves. However, using a single deep learning model may not always be accurate, and a different model may perform better with different types of diseases or images.

Therefore, in this project, we propose a system for detecting leaf diseases using multiple deep learning models. We use the concepts of knowledge distillation and ensemble learning in our project. In deep learning, knowledge distillation is a technique used to transfer the knowledge of a larger, more accurate model (known as the teacher model) to a smaller model (known as the student model). The goal of knowledge distillation is to improve the performance of the student model by allowing it to learn from the teacher model's predictions. This technique can be useful when resources are limited, and it is not feasible to use a larger model due to its computational requirements.

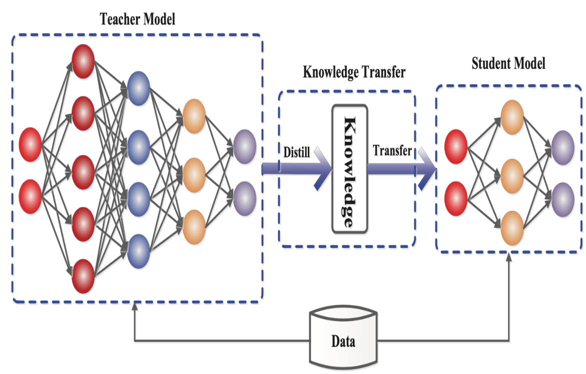

Figure 1. Ensemble Learning

Ensemble learning, on the other hand, involves combining the predictions of multiple models to improve the overall performance of the system. Each model in the ensemble may have its strengths and weaknesses, and by combining their predictions, the system can potentially achieve better accuracy, precision, and recall. Ensemble learning can be useful when the individual models have complementary strengths or when a single model's performance is limited in some way.The ensemble learning approach used in this project resulted in a more accurate and robust leaf disease detection system while requiring less computational resources and time.

Our system employs these concepts to improve the accuracy, precision, and recall of disease detection. With knowledge distillation, we transfer the knowledge of a larger, more accurate model to a smaller model, enabling it to learn from the teacher model's predictions. By ensembling the

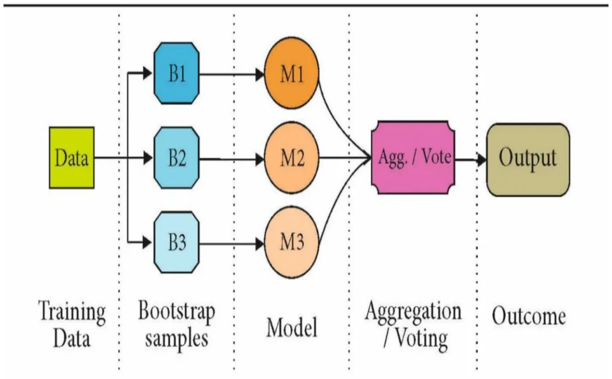

Figure 2. Ensemble Learning

predictions of multiple models, we improve the overall accuracy and reliability of our system.

We have developed an interface that allows users to select different models to detect leaf diseases, and our results demonstrate that the ensembled model achieves comparable accuracy, precision, and recall to the larger teacher model, while requiring less computational resources and time. Our proposed system provides an efficient and reliable way to detect leaf diseases in plants, potentially leading to significant benefits for agriculture and food security.

2. Literature Review

Ensemble learning has become a popular technique for improving the performance of deep learning models, and several studies have explored its application in various domains. The paper "Egeria: Efficient DNN Training with Knowledge-Guided Layer Freezing" proposes a new method for training deep neural networks that balances training efficiency and accuracy by selectively freezing certain layers. The authors demonstrate that Egeria can significantly reduce training time and memory requirements without sacrificing accuracy, outperforming several state-of-the-art techniques on benchmark datasets. The proposed approach is shown to be robust to factors such as the selection of layers to freeze and the amount of training data.

In "Deep Model Ensemble via Spatio-Temporal Variation," the authors propose an approach for ensemble learning that takes into account spatio-temporal variation in the data. Specifically, they train multiple deep models on different subsets of the data, and use a dynamic weighting scheme to combine their predictions based on the spatio-temporal features of the input. The approach is evaluated on a large-scale video classification dataset and achieves state-of-the-art performance.

"Adaptive Model Fusion for Semantic Segmentation" focuses on the problem of semantic segmentation and proposes an adaptive model fusion approach. The authors train multiple deep models with different architectures and input scales, and use a learnable fusion layer to combine their predictions. The fusion layer is trained to adaptively weight the contributions of each model based on the input image. The approach is evaluated on several benchmarks and achieves competitive results compared to state-of-the-art methods. In "Adversarial Weight Perturbation Helps Ensemble Learning," the authors investigate the use of adversarial weight perturbation to improve the performance of ensemble learning. They propose a method for generating adversarial examples that perturb the weights of the models, and use these examples to train an ensembled model with improved performance. The approach is evaluated on several datasets and achieves state-of-the-art results.

3. Major Objectives of the project

The main objective of our project is:

1. Developing a leaf disease detection system using deep learning models: The main objective of the project is to develop a system that can accurately detect leaf diseases using deep learning models. This would involve training the models on a large dataset of images of healthy and diseased leaves.

2. Improving the accuracy, precision, and recall of the detection system through the knowlegde Distillation and Ensemble learning which can help improve the overall performance of the system by combining the predictions of multiple models.

3. Comparing the performance of the ensembled model to the teacher model and the models obtained by knowledge distillation where we aim to compare the performance of the ensembled model to determine whether the ensemble approach is more effective in improving the performance of the detection system.

4. The project aims to develop a user-friendly interface that allows users to choose different models for detecting diseases, providing flexibility and ease of use. This would involve designing and implementing an interface that is intuitive and easy to navigate.

4. Dataset Collection

Dataset to be used:

https://www.kaggle.com/datasets/csafrit2/plant-leaves-for-image-classification

The plant leaves dataset on Kaggle consists of 4,503 images of 12 plant species, namely Mango, Arjun, Alstonia Scholaris, Guava, Bael, Jamun, Jatropha, Pongamia Pinnata, Basil, Pomegranate, Lemon, and Chinar. The images in this subset have been labeled into two classes - healthy and diseased. The plants were named from P0 to P11 and the dataset was divided into 22 subject categories ranging from 0000 to 0022. The images labeled with categories

0000 to 0011 represent the healthy class, while those labeled with categories 0012 to 0022 represent the diseased class. The dataset contains 2,278 images of healthy leaves and 2,225 images of diseased leaves.

5. Approach

In this project, we have developed the leaf disease detection system using the well-known deep learning model such as DenseNet121 (which is the teacher model here), the shuffleNet and mobileNet model made through knowledge distillation with the teacher model and the ensembled model to classify images of leaves into healthy or diseased categories and identify the specific disease. Having experimented with the individual models, we have found out the results. Now, to improving the accuracy, precision, and recall of the detection system, we have tried to use the Ensemble learning which can help improve the overall performance of the system by combining the predictions of multiple models.

5.1. Training Process

Training of the deep learning models was performed using a dataset mentioned above. Here, We first trained the DenseNet121 as the teacher model for the purpose of classifying images of leaves. For the knowledge distillation models, we used the pre-trained DenseNet121 model as our teacher model and trained smaller models, such as shuffleNet and mobileNet models, through knowledge distillation. However, during this detection process, we encountered some anomalies. As a result, we decided to use the concept of freezing and unfreezing layers, given that the pre-trained models were used for different tasks. Freezing a layer prevents training updates. Only the unfrozen layer weights and biases are updated. This helps preserve pre-trained knowledge while fine-tuning the model for a new task.Unfreezing a layer lets us adjust its weights and biases during training. This is useful when we wish to fine-tune the pre-trained model for a new task or dataset, especially if the new dataset is very different from the original dataset.

Thus, in our current work, we use freezing and unfreezing layers. We do this to preserve pre-trained knowledge while adapting the models to our new dataset, which differs from the original training dataset. After doing this, our model's performance improved significantly. We will unfreeze each model's convolutional layers and freeze the last few fully connected layers. We can use the pre-trained models' learnt features while adjusting them to leaf disease classification.

For the ensembled model, we combined the predictions of the teacher model, shuffleNet, and mobileNet models. The final prediction was made based on the majority vote of the three models. We used the same training parameters as the individual models.

5.2. Evaluation

Once we have trained each model, we will use a majority vote of the three models to combine their predictions. Then, we calculate the precision, recall, and F1 score of each model and compare them.

5.3. Interfacing

Now, we have developed the user-friendly interface for this system which allows the users to choose different models for detecting diseases, providing flexibility and ease of use. This would involve designing and implementing an interface that is intuitive and easy to navigate. The users takes a look at the different diseases. Now, if they select any model and enter the leaf image with disease, it will show the detected label for that leaf.

Link for the Demo: https://shilajit77-leaf2-trying-cy1r0u.streamlit.app/

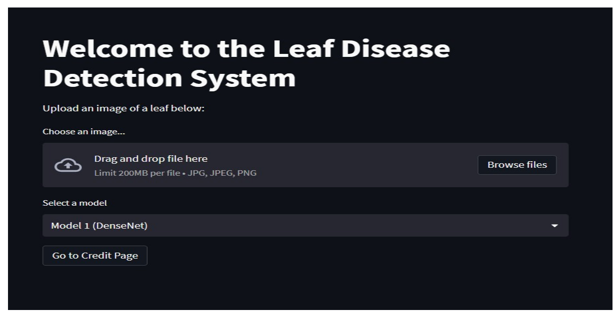

Figure 3. Interface

6. Expected Results

The evaluation results are shown in the Table 1 which has the accuracy, precision, recall, and F1 score of each model.

Model	Accuracy	Precision	Recall	F1 Score
DenseNet 121	0.88	0.91	0.88	0.88
MobileNet	0.79	0.80	0.80	0.80
ShuffleNet	0.78	0.81	0.79	0.79
Ensemble	0.90	0.91	0.90	0.90

Table 1. **Performance metrics for the models**

For the interface, we select our model, enter the test data and obtain the leaf class and its health status.

7. Conclusion

we have proposed a system for detecting leaf diseases using deep learning models and have shown that our approach of utilizing knowledge distillation and ensemble learning

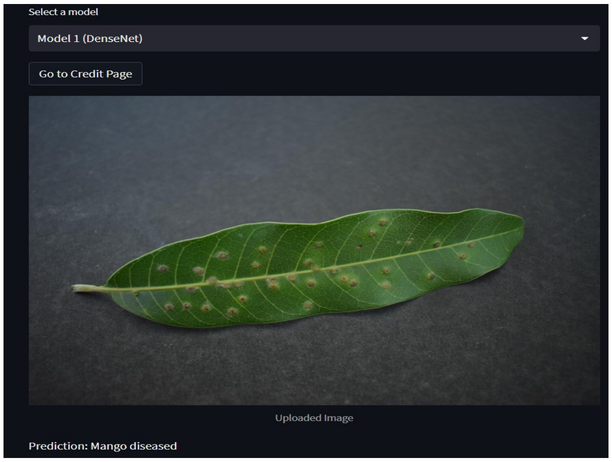

Figure 4. Result 1 by DenseNet

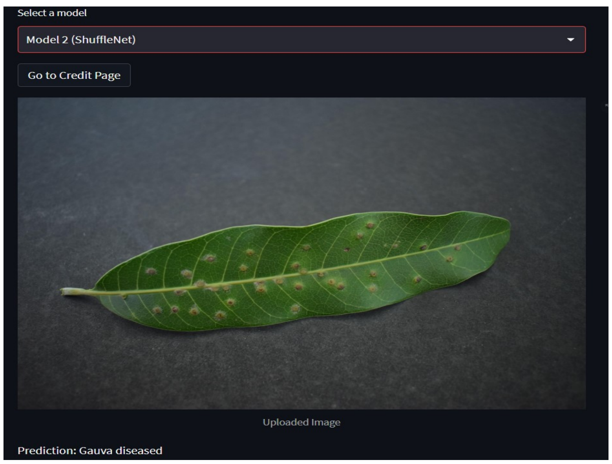

Figure 5. Result 2 by shuffleNet

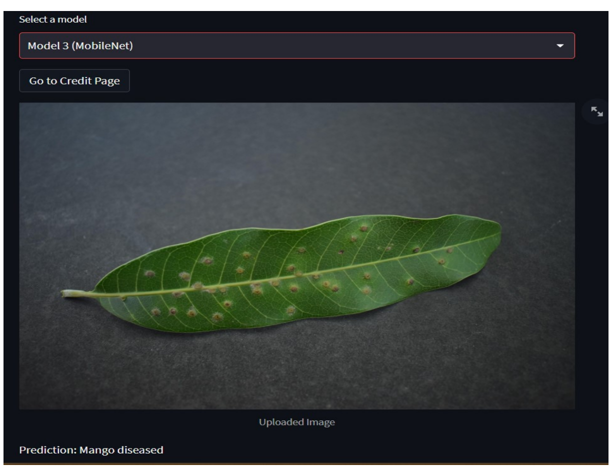

Figure 6. Result 3 by MobileNet

can significantly improve the accuracy, precision, and recall of the system. Our experiments demonstrate that the

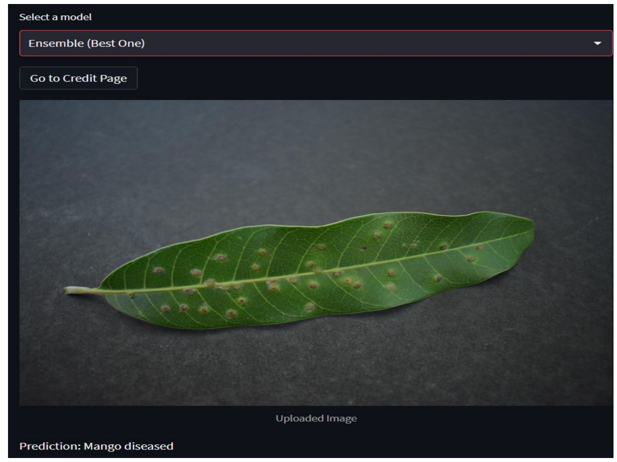

Figure 7. Result 4

ensembled model achieves comparable performance to the larger teacher model. Our system provides an efficient and reliable way to detect leaf diseases in plants, which can potentially lead to significant benefits for agriculture and food security.

8. Reference

1. ”Deep Model Ensemble via Spatio-Temporal Variation” by Jianfeng Zhang, Shuo Wang, Xiaolin Hu, Jianfei Cai, and Hongbin Zha, published in the Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR) in 2018.

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3. ”Self-ensembling for Few-shot Learning” by Marcin Andrychowicz, Misha Denil, Sergio Gomez, Matthew W. Hoffman, David Pfau, Tom Schaul, and Nando de Freitas, published (NeurIPS) in 2016.

4. ”Deep Model Ensemble for Forest Classification from LiDAR Data” by Zhijie Deng, Bo Du, and Peng Gong, published in (ICPR) in 2018.