Leveraging Transfer Learning and Knowledge Distillation for Leaf Disease Classification

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Motivation

- Automated farming equipment should have the ability to determine the health of crops.
- Existing models tend to be large and mostly unfit for application aboard lightweight vehicles.
- Smaller models are required for real-world applications such as being integrated with drones or used on smartphones.

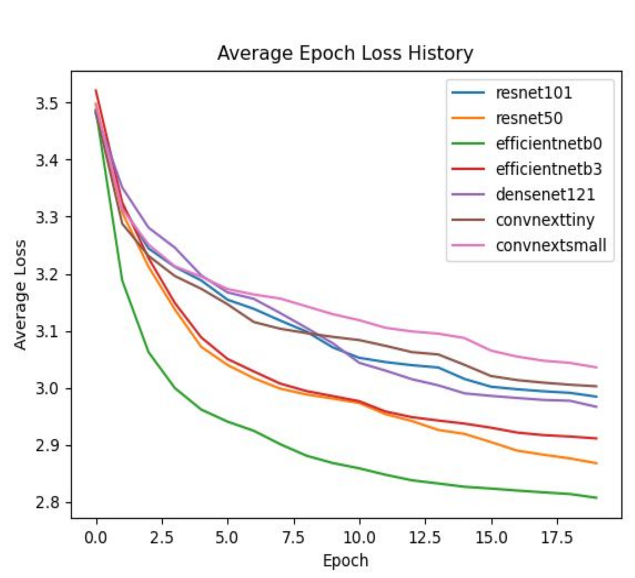
Original Methods

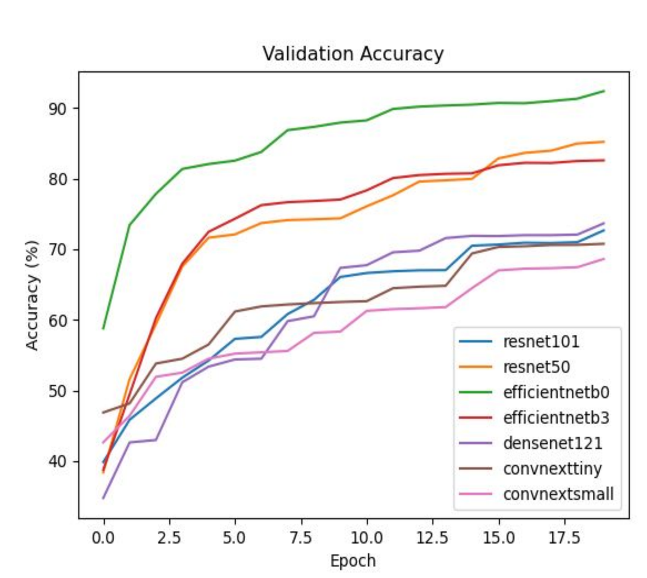
- DeepCNN built by Vishnoi [1] achieved 98% accuracy after training for 1,000 epochs.
- Dataset had 3 different classes of diseased apple leaves, along with a healthy leaf class.
- Total of 3,171 diseased and healthy images of apple leaves.
- Model only handled a small set of leaves and diseases, and was not generalizable to real-world data.

Proposed Methods

- Use a larger dataset of 54,303 images with 38 distinct classes of diseased and healthy leaves.
- Build DiseasedCNN: a model with a ResNet50 backbone, fine-tuned to identify a larger variety of species and diseases.
- Train a lightweight model by applying Knowledge Distillation, using DiseasedCNN as the teacher model.

Benchmark Testing of Pretrained Backbones

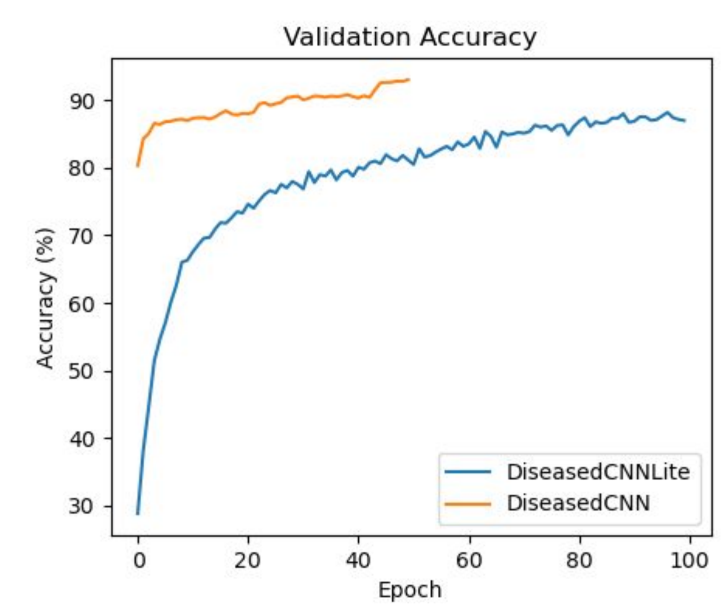




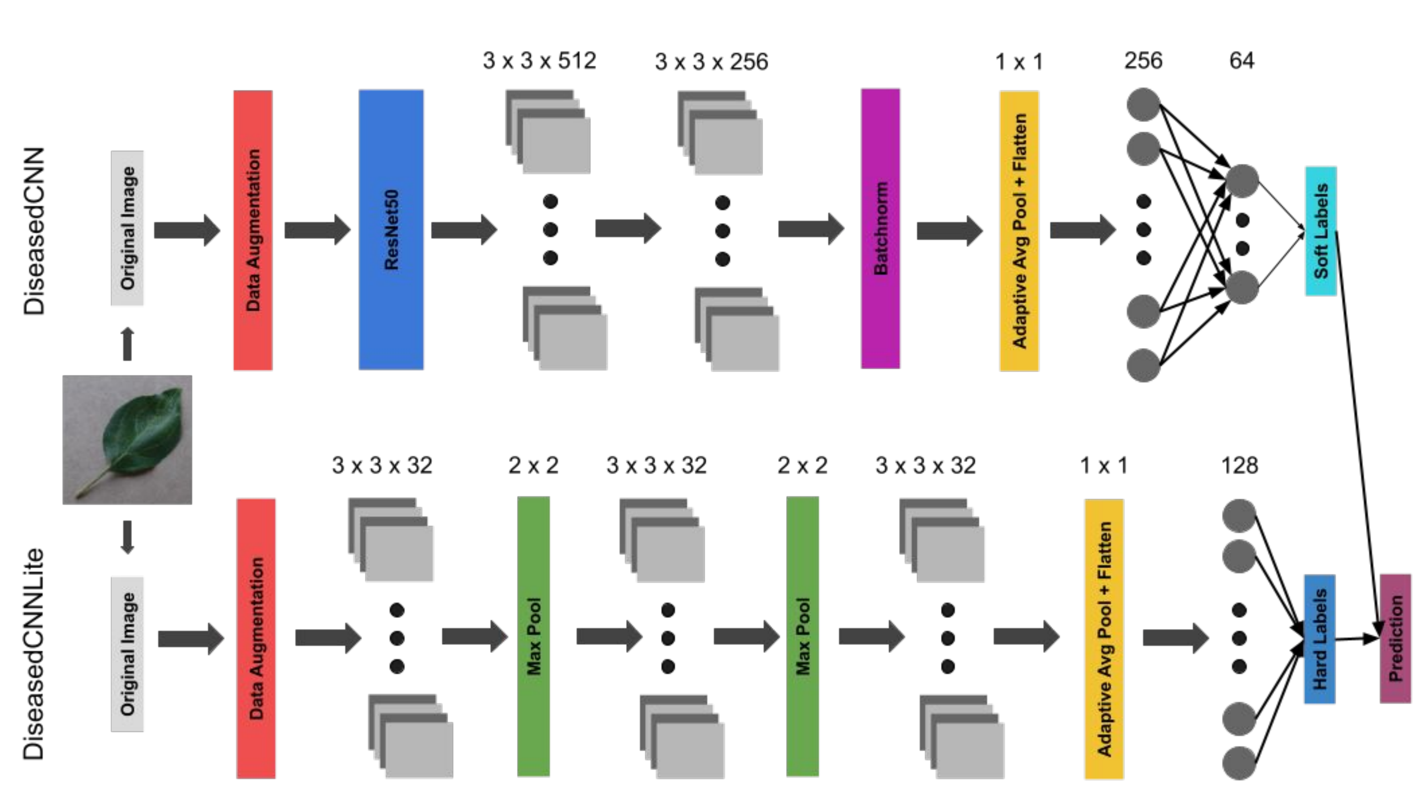
Results

- DiseasedCNN trained for 50 epochs and achieved a test accuracy of 93% on 38 different leaf classes.
- The final model size for DiseasedCNN was 130 MB.
- DiseasedCNN-Lite trained for 100 epochs and achieved 87% accuracy, and the final model size was 390 KB (334x smaller than DiseasedCNN).

	DiseasedCNN	DiseasedCNN-Lite
Learning Rate	0.0005	0.0005
Learning Rate Decay	0.9	0.9
Weight Decay	-	0.00001
Temperature	-	4
Alpha	-	0.7



DiseasedCNN and DiseasedCNN-Lite Knowledge Distillation Architecture



Reproduction Discussion

- The DeepCNN reproduction achieved an accuracy of 94%, after training for 250 epochs.
- The DeepCNN model significantly overfit when trained for the specified number of epochs (1,000).
- Due to a lack of specification in the paper, our data augmentation may have differed slightly, thus potentially causing this disparity in results.

Extension Discussion

- EfficientNet-b0 performed best during benchmarking, but we discovered that ResNet50 performed best in context with DiseasedCNN's fine-tuning layers.
- Learning rate scheduling led to much higher accuracy.
- Putting more emphasis on hard loss as opposed to soft loss led to more effective knowledge distillation.

Future Work

- Integrating DiseasedCNN-Lite with real robots or drones.
- Expanding the network to identify more leaf species and types of diseases.
- Benchmarking the computation time and power requirements needed to run on a robot or drone, and optimizing further.

Acknowledgements

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References

[1] Vibhor Kumar Vishnoi; Krishan Kumar; Brajesh Kumar; Shashank Mohan; Arfat Ahmad Khan. Detection of apple plant diseases using leaf images through convolutional neural network. IEEE Access, 11:6594–6609, 2022.

[2] Mohit Singh. Plant village dataset. Technical report, Kaggle, 2021