Genetic Algorithm Optimized Stacking Approach to Skin Disease Detection

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SCOPE

INTRODUCTION

- Skin diseases are a common occurrence among people
- Skin diseases are responsible for almost 98,000 deaths worldwide and about 18,000 deaths in India in 2019
- Skin diseases can cause disability and decrease the quality of life and life expectancy
- Disability-Adjusted Life Years (DALY) is a metric used to quantify the burden of a disease
- In 2019, skin diseases were responsible for 1.79% of the global burden of diseases and 1.49% of the burden of disease in India
- Deaths caused by skin diseases have increased over the years

Motivation:

- Existing solutions for skin disease detection use small datasets, which may result in lower precision and accuracy due to underfitting
- Some systems can only detect a small number of skin diseases, decreasing their robustness
- Some systems cannot handle environmental and texture-based changes in input images, which is a major factor as environment and lighting conditions cannot always be controlled
- Some systems use models that may not be powerful enough to detect the comprehensive list of skin diseases

OBJECTIVES

Our objectives while creating the deep learning system was to utilize a dataset that is comprehensive in terms of coverage of the various skin diseases, a crucial part of the system due to the numerous skin diseases that can affect humans. The system must be capable of detecting the multiple skin diseases to increase usability of the system in the crucial scenarios. Apart from this, the system would have to be dependable and reliable which can be achieved by bettering the model accuracy.

SCOPE OF THE PROJECT

- Helps small-large scale clinics, get a primary diagnosis on possible skin diseases.
- Helps the patient get a good primary understanding of what they might have, and approach the doctor with the primary diagnosis.

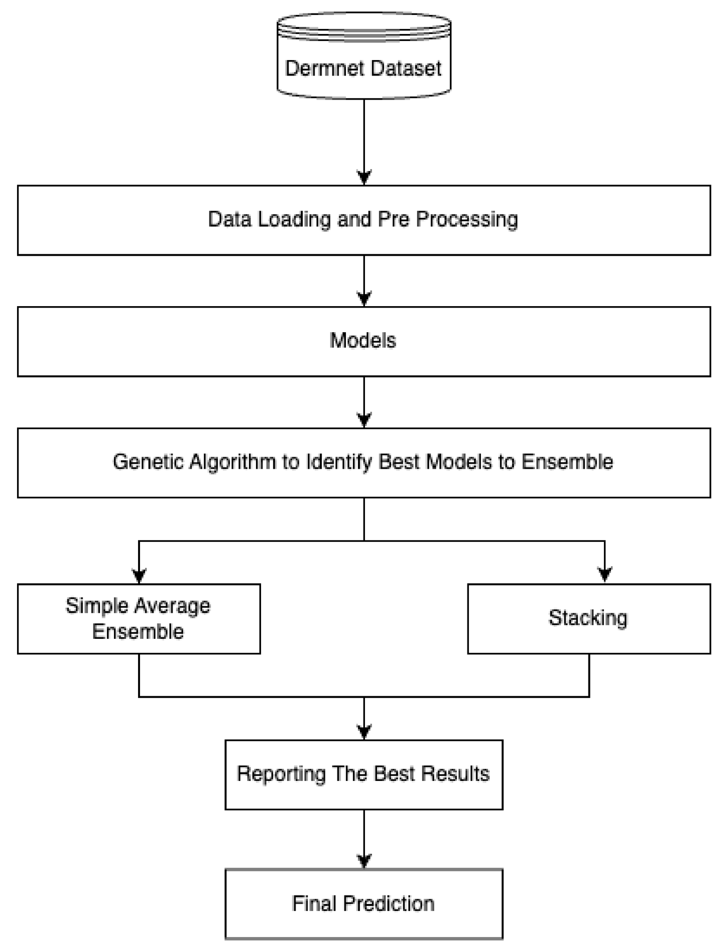
METHODOLOGY

In the proposed system, the following modules are implemented.

- Image source module – Performs sourcing of the image.
- Preprocessing Module – Processes the input image before it is fed to the machine learning model for prediction or training.
- Prediction Aggregator module for ensemble models – To be used with models which use an ensemble approach for prediction of the input image.
- Prediction Module – Provides the prediction from the machine learning model given the input image.

The machine learning model for the proposed system consists of an ensemble model of ResNet50, DenseNet121 and a basic CNN. To identify better performing combinations of models, a Genetic algorithm-based approach was used to effectively produce accurate ensembles. The genetic algorithm can identify models which could better perform when used together compared to individual performances which also helps overcome the inefficiencies of single models.

ARCHITECTURE



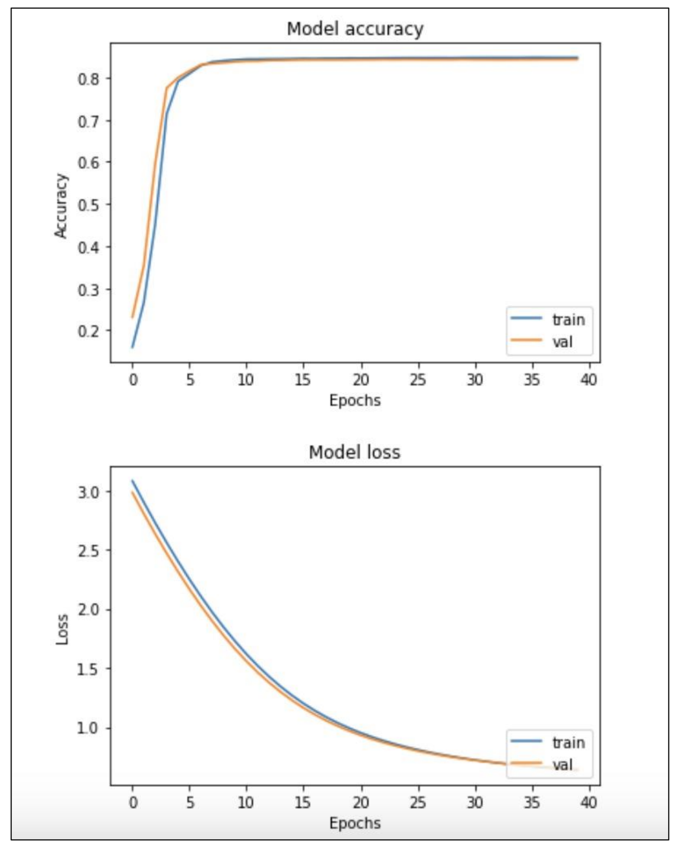
1. Loading of the DermNet dataset and preprocessing the images which performs encoder transformation and rescaling of pixels before being fed into the model. This ensures uniformity of the input images to better fit the model.
2. Data which is preprocessed is then split into train and test sets. The model is trained on the train dataset, while the test dataset is used to evaluate the model's performance after the training is completed.
3. Training is then performed on the train data with one of the models. The loss and accuracy at every epoch in the training is saved. Once the models have been trained, they are then evaluated based on their accuracy on the test dataset. This metric is used in the next step by the genetic algorithm.
4. The genetic algorithm uses the performance metrics of the model to identify the best combinations of these models which can enhance overall performance of the system.
5. Models selected by the genetic algorithm are then stacked together or are put into an ensemble. The ensemble uses majority voting where every model outputs a most probable class according to itself and the class with the most votes is chosen as the final output.

RESULTS AND DISCUSSION

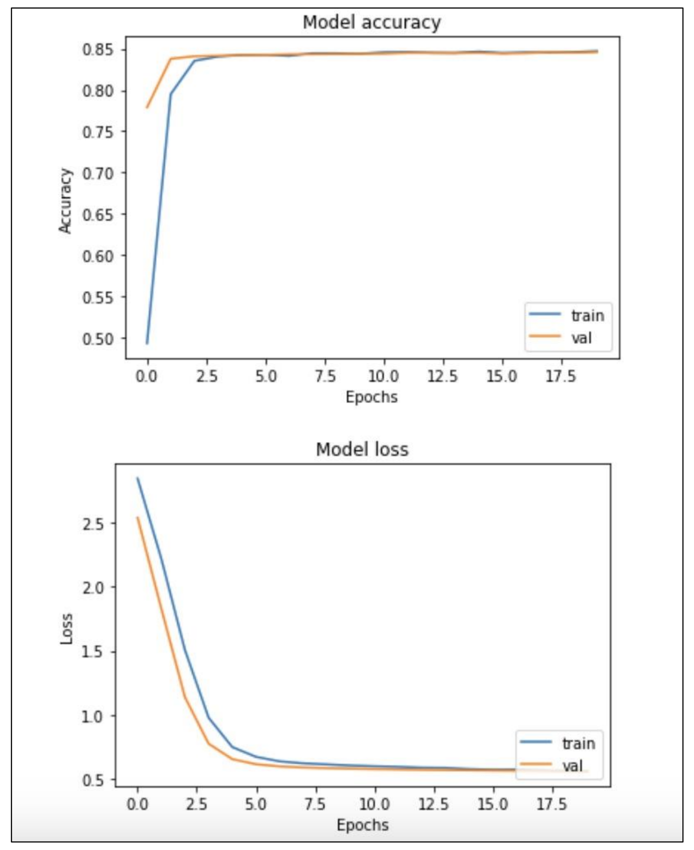
Batch Size	256
Learning Rate	0.001
Optimizer	Adam
Loss function	Categorical Cross Entropy
Train Test split ratio	80% for train 20% for test

	Model	Loss	Accuracy	Top 5 accuracy
Base Case	CNN	2.8575	0.3448	0.6489
Using Pretrained Models as Feature Extractors	Resnet50	2.7414	0.1777	0.5275
	Densenet121	3.2352	0.3256	0.6387
Retraining Some Layers of a Pretrained Model	Densenet121 unfrozen	3.1213	0.4015	0.7216
	MobileNet unfrozen	11.1857	0.3381	0.6564
	Efficientnet v2 unfrozen	4.0056	0.1709	0.4670
	Resnet101 Unfrozen	3.3396	0.1469	0.4693
	Resnet50v2 unfrozen	3.1352	0.3966	0.6989
Simple Average Ensemble	Ensemble of Resnet50, Densenet121 unfrozen and CNN	2.1539	0.4538	0.7354
	Genetic Algorithm ensemble of CNN, Resnet50, Resnet50v2 unfrozen and Densenet121 unfrozen	2.0189	0.4545	0.7339
Stacking Based Ensemble	Stacking of Resnet50v2 unfrozen, Densenet121 unfrozen and CNN	1.9963	0.4578	0.7389
	Stacking of CNN, Resnet50, Resnet50v2 unfrozen and Densenet121 unfrozen	2.0202	0.4583	0.7401

The accuracies improved because of the ensemble approach performed on the ResNet50, DenseNet121 and basic CNN models compared to the individual accuracies of the models. The DenseNet121 model performed well as a standalone model with an accuracy of 0.4015 and a Top-5 accuracy of 0.7216. The ensemble approach which combined the ResNet50, DenseNet121 and a basic CNN gave an accuracy of 0.4538 and a Top-5 accuracy of 0.7354.



Stacking ResNetV2 Unfrozen, DenseNet121 Unfrozen and Basic CNN



Stacking of Genetic Algorithm derived models - ResNet50V2 Unfrozen, DenseNet121 Unfrozen, Basic CNN and ResNet50 Frozen

CONCLUSION

A skin disease detection system is required to have a high accuracy due to the importance of the decisions. To implement a system for skin disease detection, multiple models have been explored which were utilized in other similar applications, along with approaches like ensemble of models and genetic algorithm approach to find better performing combinations of these models. Individually the models

With the usage of stacking and ensemble approach where multiple models were combined, the cumulative performance of the models has been improved.

A different approach to the proposed system can be explored by implementing a stacking-based or weight average-based ensemble techniques. The ensemble approach can also be further explored by making use of other different neural network architectures.

REFERENCES

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2. Srinivasu, P.N., SivaSai, J.G., Ijaz, M.F., Bhoi, A.K., Kim, W., and Kang, J.J., 2021. Classification of skin disease using deep learning neural networks with MobileNet V2 and LSTM. Sensors, 21(8), p.2852.