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Ensemble learning for the classification of Alzheimer disease

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ABSTRACT

This project uses ensemble learning technology and combines three models (ResNet, AlexNet, and MobileNet) to classify and recognize magnetic resonance imaging (MRI) of Alzheimer's disease. The dataset contains 33984 MRI images, with a 6:2:2 ratio used for the training, validation, and testing sets, respectively. By integrating models, this project achieved a recognition accuracy of 99.65%. This project will help healthcare professionals apply Alzheimer's disease identification methods in automated systems, thereby saving more medical resources and time, and providing better medical services for patients.

INTRODUCTION

The project aims to effectively classify Alzheimer's disease using a set model, achieving four classifications: NonDetermined, MildDetermined, ModerateDetermined, and VeryMildDetermined, in order to take early measures to reduce mortality and reduce medical resource costs.

DATASET

This dataset is gotten from Kaggle dataset and it contains 33984 cross-sectional MRI images of the brain with Alzheimer's disease. 8960 MRI images contains mild dementia, 6464 MRI images is moderate dementia, 9600 MRI images is non-dementia, and 8960 MRI images is the very mild dementia. The split ratio for the training set, validation set, and test set is close to 6:2:2.

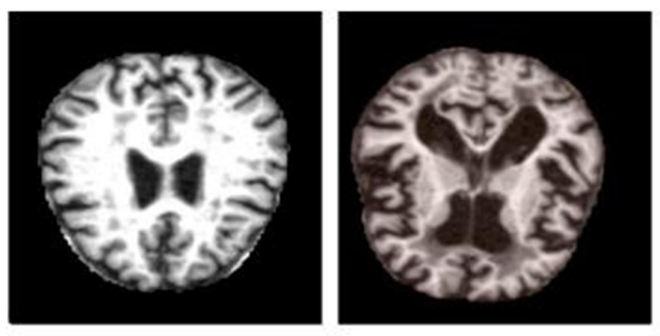

Figure 1: Sample of Alzheimer's image in dataset

METHODOLOGY

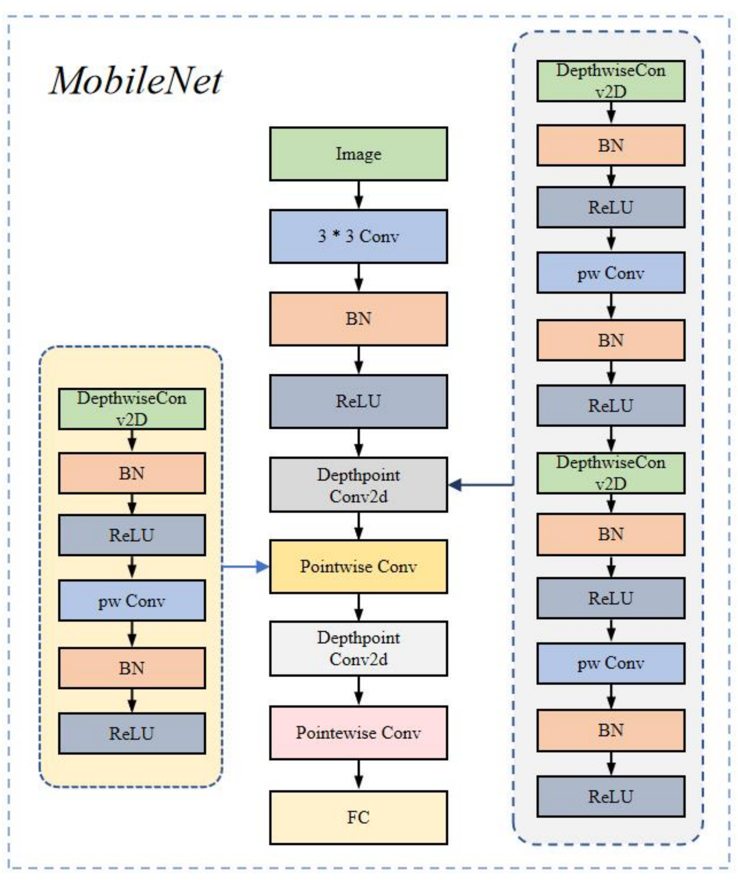

Figure 2: The Finetuned MobileNet

The MobileNet structure uses depthwith separable convolution to replace the standard convolution operation, and calls these two structures repeatedly to reduce the amount of model parameters and increase the amount of model calculation.

Each layer is followed by a batchnorm and a ReLU nonlinear layer. Finally, the Flatten layer and the full connection layer are used to classify the images. Point convolution and deep convolution structure are the core of MobileNet, which makes MobileNet more efficient and more suitable for mobile devices. Point convolution is mainly responsible for integrating the information in the feature map, while depth convolution is responsible for extracting features. The Finetuned MobileNet Architecture used in this project is shown in Figure 2.

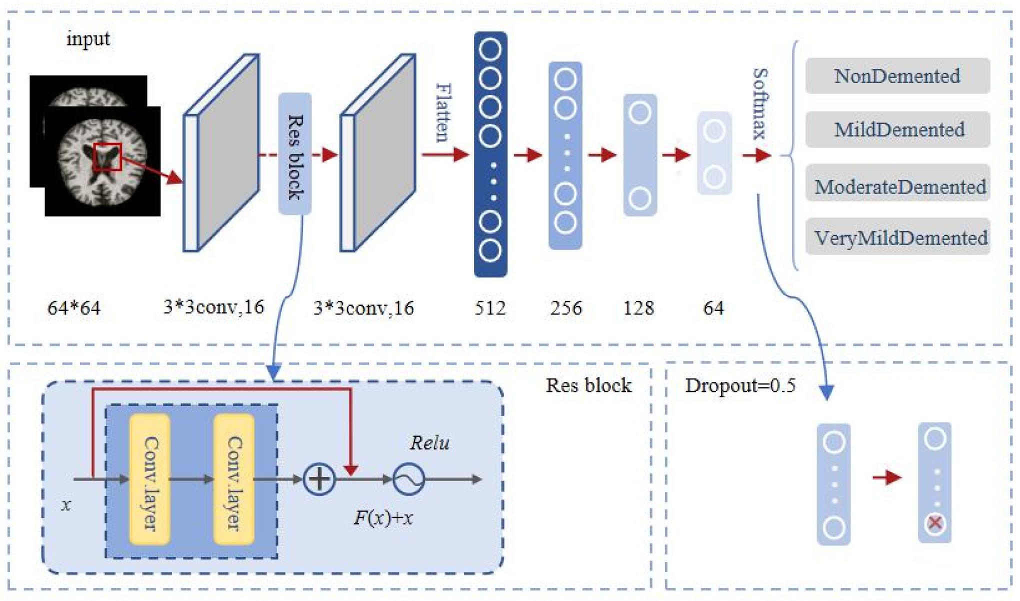

Figure 3: The Finetuned ResNet

The residual network(ResNet) is constructed from Residual Building Blocks, it does not increase the complexity of the network while increasing the depth of the network. The quick connection of ResNet makes the network easier to optimize. The internal residual block uses a skip connection, which alleviates the problem of gradient disappearance caused by increasing depth in the deep neural network.

AlexNet has an eight layer structure. The first five layers are convolutional neural networks, and the sixth to eighth layers are traditional neural networks. It uses the ReLU activation function to prevent the gradient from disappearing and the Dropout to prevent over fitting. The whole network can be seen as the input layer is operated by convolutional layers, followed by a series of fully connected layers, and finally the output layer is used to obtain the prediction result.

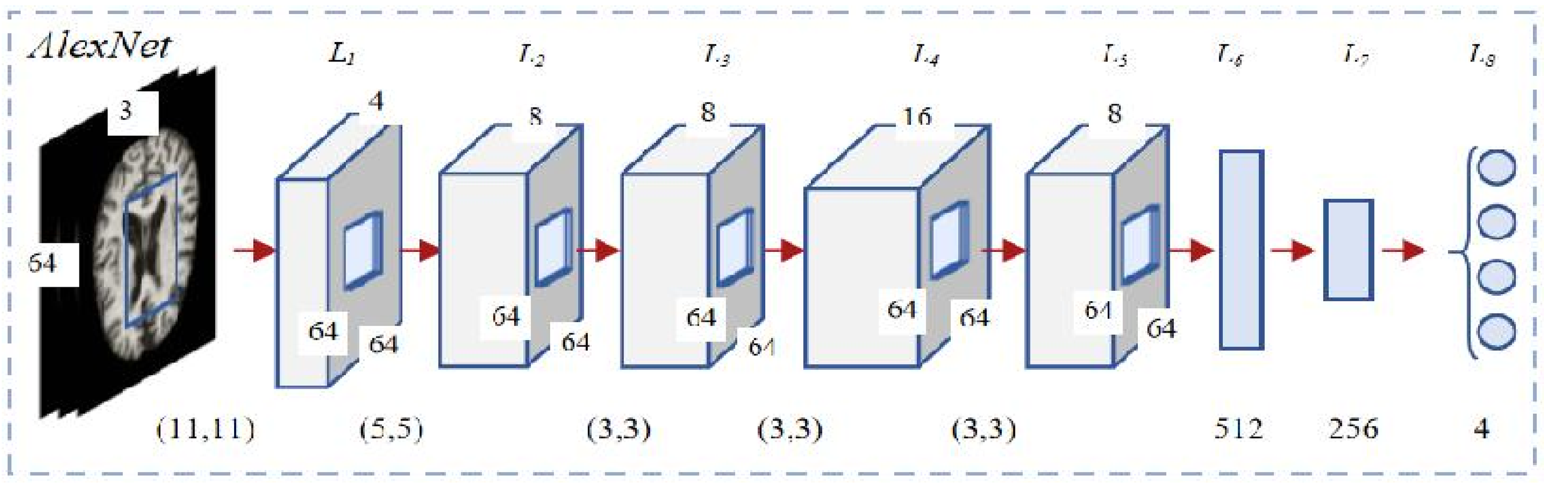

Figure 4: The Finetuned AlexNet

ARCHITECTURE

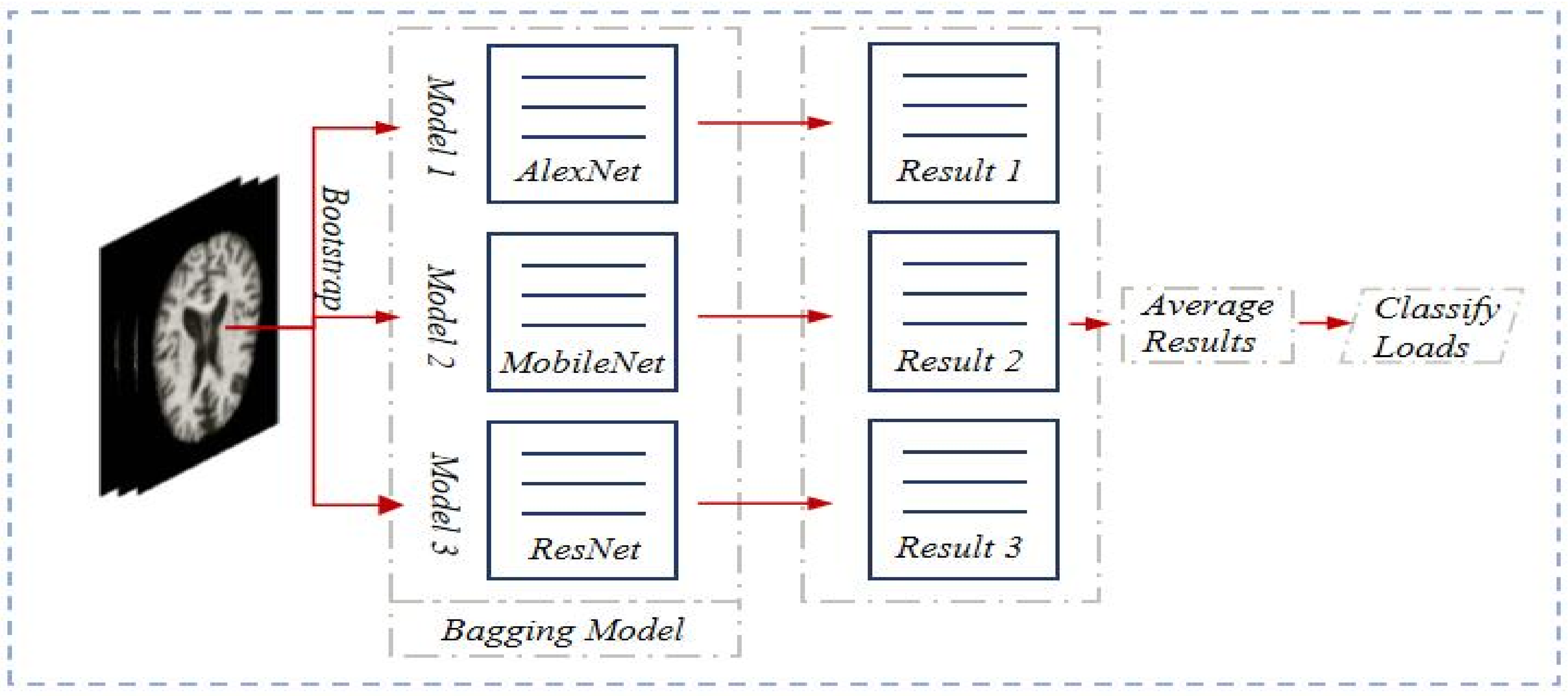

Figure 5: The Ensemble structure

This project classifies image files through three pre-training models, fine-tuned ResNet, AlexNet and MobileNet, and uses a voting scheme combined with the output of the three models to determine the prediction classification. After the adjustment of the image size, three models were used to predict the probability distribution of the image belonging to the four predefined categories. Each model will generate the probability distribution of four categories, calculate the number of votes for each category label and update the voting list, completing the multi-model voting integration.

RESULT

	ResNet	AlexNet	MobileNet	Ensemble	Loddo et. al., [4]	Li et. al., [5]	Razzak et. al., [6]
Accuracy	0.99281250	0.99546875	0.95484375	**0.9965625**	0.9867	0.9861	0.979
Loss	0.02714268	0.01434312	0.14991681	-	-	-	-
Precision	0.99282491	0.99548415	0.95528153	**0.99656293**	-	-	-
Recall	0.99281250	0.99546875	0.95484375	**0.9965625**	-	-	-
F1-score	0.99280679	0.99547028	0.95484705	**0.99656138**	-	-	-

Table : Final comparison

The table shows the best results of three individual models after adjustment and training. Compared with the ensemble project, the integrated strong learner obtains higher evaluation data than the single model, and the ensemble effect of the project is confirmed.

DISCUSSION

Ensemble learning has a wide application prospect in MRI image recognition of Alzheimer's disease. In the future, the integrated learning algorithm can be further optimized to achieve higher accuracy of MRI image recognition for Alzheimer's disease. In addition, with growing medical data sets, more data and more advanced deep learning models can be used to further improve predictive performance. Ultimately, MRI image recognition for Alzheimer's disease could provide clinicians with better diagnostic and treatment options

CONCLUSION

During the course of the project, three models were used: ResNet, MobileNet and AlexNet. By fine-tuning the model and combining their predictions, it is possible to achieve a reliable, accurate quadrilateral diagnosis of MRI images of Alzheimer's disease. At the same time, by comparing the performance of single model and ensemble learning model, it is found that ensemble learning has significant advantages, which proves the superiority of ensemble learning from multiple indicators. This is a meaningful project given the increasing impact of Alzheimer's disease on society and individuals. The program's 99.65% accuracy of the quadrotaxa can be used as one of the most trusted diagnostic tools available to healthcare professionals, and the GUI is designed to enable healthcare professionals and patients and their families to make better use of the tool.

GUI

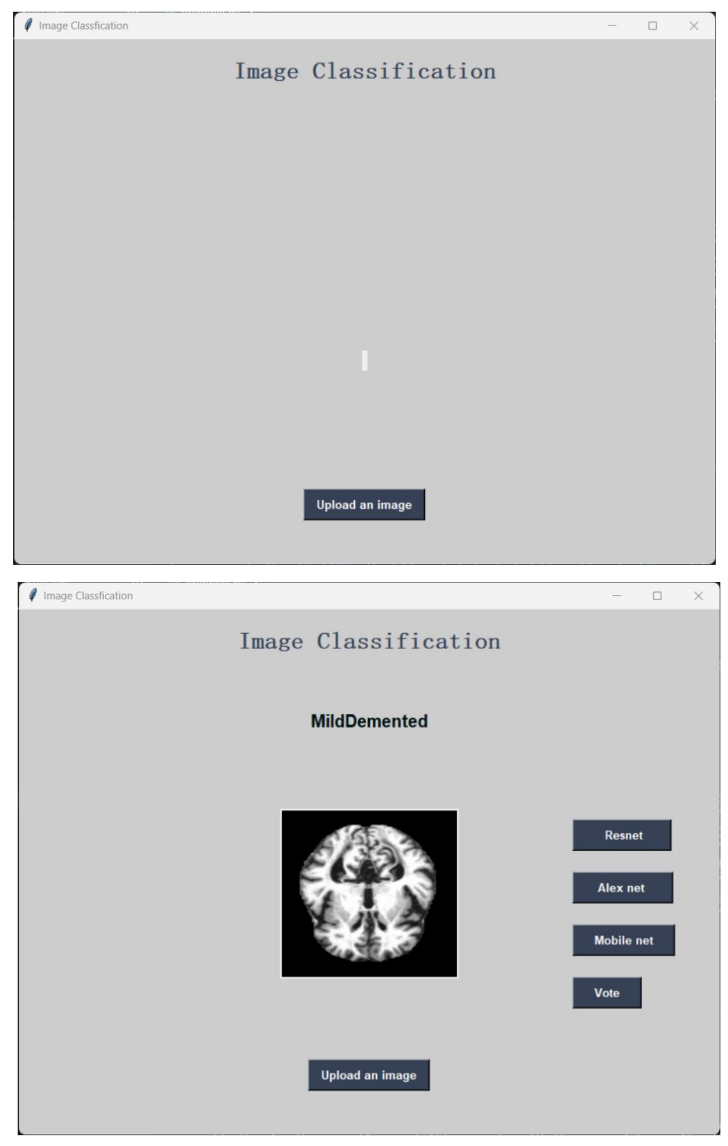

Figure 6-7: The GUI

REFERENCES

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