A Novel Deep-Learning Based Classification Of Alzheimer's Disease In Adults

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***Abstract*—Alzheimer's Disease (AD) is a neurodegenerative disease that is the cause of impairment of cognitive abilities and deterioration of memory. AD is most often observed in people beyond the age of 65. Diseases like AD are best treated by starting the treatment early. Delaying the treatment due to minor uncertainty can accelerate the deterioration. Using AI, medical professionals can confirm the presence or absence of the condition and immediately start the treatment.**

In this paper, Sequential Deep Convolutional Neural Network was used to perform a 5-way classification. Data from two varied sources was combined. The data was oversampled using Synthetic Minority Over-Sampling technique from imblearn. The Deep CNN model was able to achieve a maximum of 93.57% accuracy while being tested on data from both data sources. Thus, Deep CNNs are able to classify brain MRI images from varied data sources with sufficient accuracy.

Keywords— Classification, Brain MRI, Alzheimer's Disease, Deep CNN, Deep Learning

I. INTRODUCTION

Alzheimer's disease (AD) is a neurodegenerative disease, which means that it causes a progressive loss of structure and functions of neurons, slowly leading to death. It is most commonly caused by dementia which is progressive impairment in memory. It most often affects the short-term memory. People affected by AD may have problems understanding the language; this neurological syndrome is called dementia. "AD is a brain disorder that slowly destroys memory and thinking skills and, eventually, the ability to carry out the simplest tasks" [1]. "Alzheimer's is the most common cause of dementia, a general term for memory loss and other cognitive abilities serious enough to interfere with daily life" [2]. Persons affected with AD are said to be disoriented and lose the capability to understand time, directions, people, and place. The symptoms may include mood swings, which means that AD will frequent change in the person's mood. The patient may lose his/her confidence. Their condition deteriorates further as they neglect themselves. A patient who has AD exhibits abnormal behaviour. Apolipoprotein [3] is a sub-type of AD. Some factors like head injury, depression, and high stress may be causes for AD. "Research supports the theory that an imbalance in the production and clearance of amyloid-beta is central to the development of AD" [3]. In the brain of a person affected with AD, protein builds up around the brain cells. Due to AD, "there is a loss of neuron connection in the brain" [1] where an electrical or chemical signal passes to another neuron.

AD patients may benefit from exercise programs. It helps the patients recover or reduce the symptoms of the disease. Due to abnormal behavior and impairment of memories in the brain may cause problems in daily living and lead to an earlier death (3-10 years after the disease [4]). Often AD begins in people more than 65 years of age. Due to short-term severe memory-loss and dementia, the neuron cell dies in the brain. AD is a disease wherein the earlier stages are just mild memory loss. In the final stage of AD, the patient fails to remember the conversations he/she was having.

There may be problems in understanding the language, worsening of vocabulary, decreased word frequency, and gradual deterioration of reading and writing skills [5]. Difficulty in speech increases. In the middle stages, frequent use of unrelated vocabulary is noticed. In the advanced stages, they require round-the-clock care to perform daily tasks [6]. AD does not affect all memories equally. Essential memories like long-term memory, general knowledge, and episodic memory are not affected by AD in earlier stages. AD is characterized by the loss of neurons and the inability to pass electrical or chemical signals to other neurons. Altered cholesterol metabolism seems to play a fundamental role in the formation of amyloid plaques and tau hyperphosphorylation [7].

There is tremendous research being conducted all over the world to find a definitive cure for AD, but none have been identified yet. However, methods have been identified to

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prevent and even slow down the development of AD symptoms.

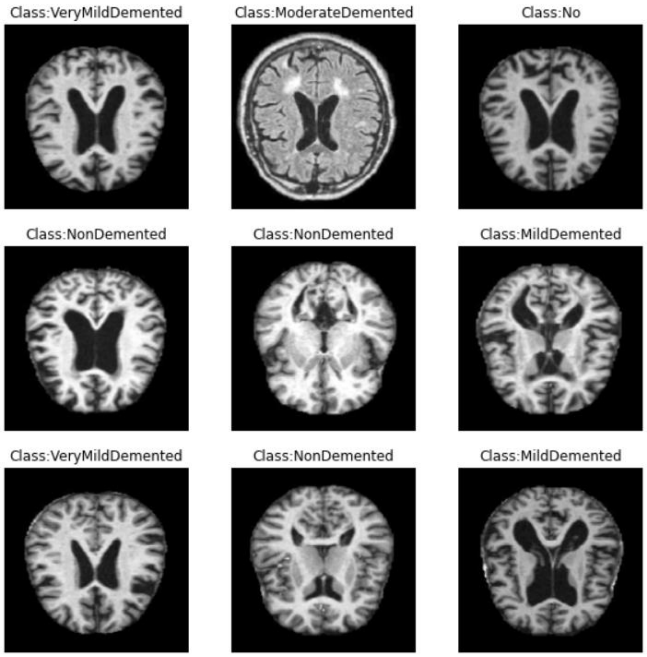

Fig. 1. Various brain MRI scans

II. Literature Survey

Alzheimer's symptoms cannot be recognised in a single lab test, scan, or examination. Non-imaging to advance capabilities to make more easily review the disease and treat as well as to improve the efficiency of clinical trials. By improving the accuracy of prediction, a qualified physician can get a second opinion and reduce the time before the treatment process begin.

There has been prior research on the classification of levels of dementia due to AD to study the accuracy obtained from using different Machine Learning algorithms. Fan, Z., Xu, F., Qi, X. *et al.* worked on classifying AD based on brain MRI [8]. They used an SVM classifier to classify and predict different disease processes of AD based on structural brain MRI data. They discovered that the SVM classifier had strong objectivity and good generalizability.

Similarly, J. Liu, M. Li, W. Lan, F. Wu, Y. Pan, and J. Wang worked on classifying AD using a whole-brain hierarchical network [9]. They employed a whole-brain hierarchical network (WBHN) to represent each subject. The connectivity between pairs of regions in the brain was correlated using Pearson's correlation coefficient and used as a classification feature. Furthermore, A. Rao, Y. Lee, A. Gass, and A. Monsch [10] worked on the classification of AD from structural MRI using sparse logistic regression with optional spatial regularization. Here, Sparse Logistic Regression was applied first and then compared with Penalized Logistic Regression (PLR) and Maximum uncertainty Linear Discriminant Analysis (MLDA). There is a significant improvement in prediction results using SRSLR than SLR, which may better reflect the regional effects of AD.

Alternatively, Tong Tong, Katherine Gray, Qinquan Gao, Liang Chen, Daniel Rueckert [11] worked on the multimodal classification of AD using nonlinear graph fusion. A multi-modality classification framework is presented to exploit the multimodal data's complementarity efficiently. Similarities from multiple modalities were then combined in a nonlinear graph fusion process, which generates a unified graph for final classification.

Ben Ahmed, O., Benois-Pineau, J., Allard, M. *et al.* [12] worked on classifying AD subjects from MRI using hippocampal visual features. An automatic classification framework for AD recognition in structural MRI was developed. It can be highlighted that visual features from the hippocampal area and the late fusion scheme significantly improve classification results.

A unique method of using Deep Learning was investigated by A. Farooq, S. Anwar, M. Awais, and S. Rehman [13], who worked on a deep CNN-based multi-class classification of AD using MRI. Here, a 4-way multimodal classifier was implemented to classify the levels of cognitive impairment with the GoogLeNet Model.

This paper presents a novel Deep CNN-based 5-way classification on four levels of demented brain and a healthy brain. It shows significant improvement in performance from the earlier 4-way classification and also classifies healthy individuals from diseased individuals by using significantly smaller amounts of MRI data.

III. Methodology

This section details the model's architecture, the data sources used, and the algorithms utilized for processing and analyzing the data.

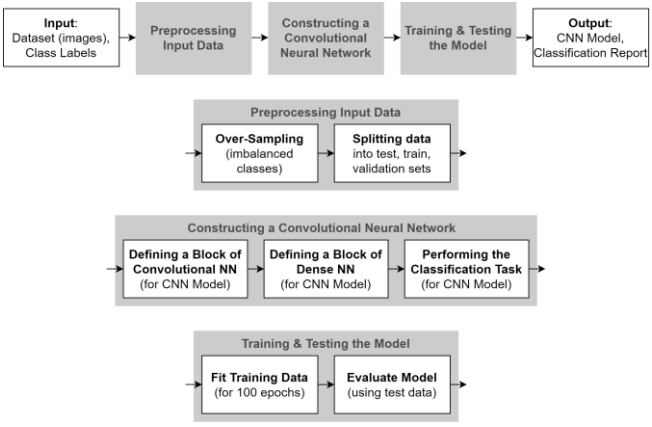

Fig. 2. Model Architecture

All classification images from (CatA) ADNI [14] and (CatB) Healthy brains dataset [15] were taken and combined (5 classes along with 'No') to study the classification capabilities between them. From Fig.2 the images were taken as inputs for the model and passed for preprocessing. Data was

segregated into various sizes, creating multiple datasets composed of the same initial source data. Table-I shows various batch configurations and images taken for each class(taking 3200/5500/6000/6400 images). Observations in some classes are much higher or lower than other classes, affecting accuracy.

TABLE I. BATCH CONFIGURATIONS USED FOR PERFORMING THE TESTS

Batch Configuration	**Category - A (CatA)**				**Category - B (CatB)**	**Total**
	NonDemented	***VeryMild Demented***	***MildDemented***	***Moderate Demented***	***Healthy (No)***	
1	882	846	807	64	792	3200
2	1656	1592	861	64	1356	5500
3	1824	1928	896	64	1380	6000
4	2080	2032	896	64	1380	6400

The dataset is oversampled to maintain all the images with almost the same number as the majority class. The oversampling method used is SMOTE (Synthetic Minority Over-sampling Technique) [9] from the imblearn library. With SMOTE, the sampling_startegy defaults to 'auto,' which is equivalent to non-majority classes; this increases the number of samples for minor classes. The data is then split into train, test, and validation sets to be classified using a Deep CNN model.

Deep Learning has been considered powerful for handling large datasets in the past few decades. All comparative machine learning methods provide very high classification accuracy, and CNN outperformed the comparative methods.

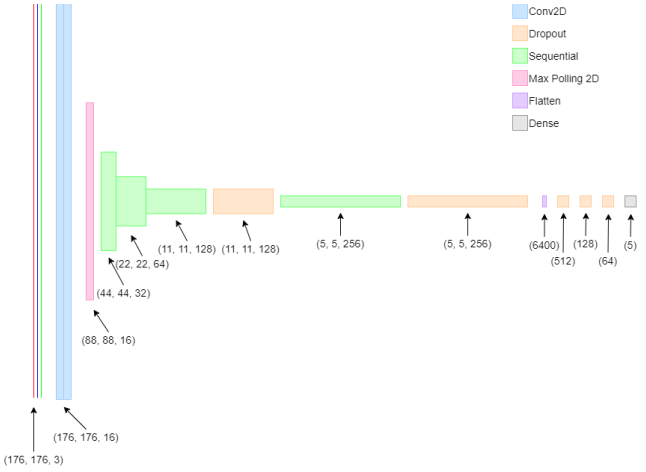

Fig. 3. Sequential CNN Layers

CNN is most commonly used to analyze pictorial data. In Fig. 3 it can be observed that each training image contains three layers with red, green, and blue. For simplicity, Grayscale images have been used to which a kernel filter is applied, i.e., a 3x3 matrix that extracts the number of similar bits.

Max Pooling technique is applied; it returns the maximum value of the pixel from the portion of the selected kernel. Average Pooling returns the average of all pixels. The main purpose of Pooling is to decrease the computational complexity. It is then fed into series of Sequential layers. Finally, the last layer is the Dense layer, the output layer (number of classes). The output gives the probability of the image belonging to a class and applies softmax, ranging from 0 to 1. The result is Sequential CNN (where the output of dense 4 for ADNI samples and 5 for the dataset with healthy brains). The activation function used for altering the weights of the connections is 'Adam' from the Keras library [17]. We tried a model altering learning rates. After model construction, we trained our model with train_data and tried to classify them. After training our model with the data, we have validated it with the validation data. After the validation step, we gave our test data for the evaluation and got the output and classification report.

IV. RESULTS

This section details the experimental results obtained after running the experiment as described in the previous section. The first few tests were related to fine-tuning the learning rate. The manual trial-and-error approach was initially followed. However, because the process was highly repetitive and inefficient, other alternatives were investigated. We run our model with different learning rates. The Adam learning rate optimizer [17] was identified to be the best suited for our application. Fig. 4 shows the outcomes of some of the trials run on a batch of 6000 images (Healthy patients included).

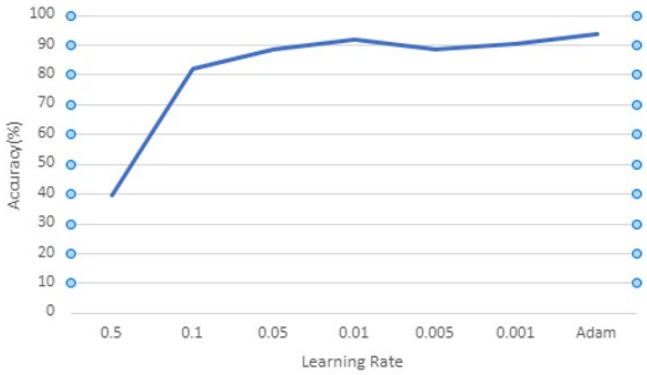

Fig. 4. Accuracies obtained for some tested learning rates

The optimal learning rate was used to train the four models and then compared their accuracies, i.e., with and without the Healthy patients' data included. Fig. 5 shows the accuracies obtained for each batch configuration. It can be observed that when smaller data samples are taken, the accuracy worsens when the CatB (Healthy) data is added. However, as the input data increases in size, the accuracy significantly improves when including the Healthy patients' data.

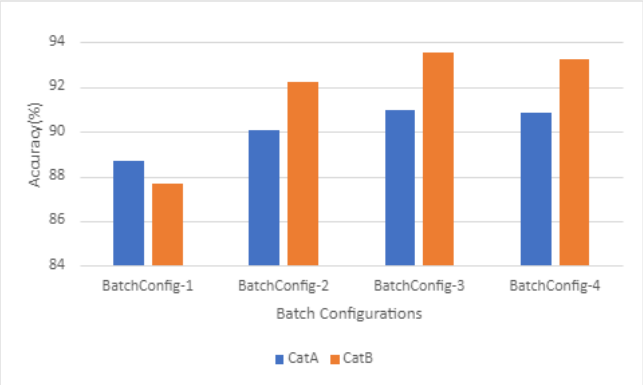

Fig. 5. Accuracies obtained for each Batch Configuration from Table-1

From Fig. 5, it can also be observed that the highest accuracy is obtained for BatchConfig-3b (6000 w/ Healthy) and is closely followed by BatchConfig-4b (6400 w/ Healthy). This dip might result from over-fitting occurring when the input data size is increased. This observation is consistent with the dip in accuracy between BatchConfig-3a and BatchConfig-4a.

Fig. 6. Confusion Matrices generated for (a) BatchConfig-3a and (b) BatchConfig-3b

From Fig. 6 and Fig. 7, it can be deduce that the model with the healthy brain can classify the classes with reasonable accuracy. True positive classification is almost identical, but the non-healthy brain model has negative values with MildDemented. However, including the healthy brain has increased the model's true positive rate. The model's accuracy (5-way classification) increases when the dataset size increases. From Fig. 5, it can be seen that ACC curves show the accuracy of the model in classifying the data. AUC provides an accumulated measure of performance across all possible classification thresholds. The higher the AUC, the better performance of the model at classifying classes. From Fig. 8, it can be noted that the BatchConfig-4b is having more noise in the curve. This says that the model is overfitting the data. By looking at Fig. 8, it can be observed that the BatchConfig-3b is performing better than BatchConfig-4b in AUC scores.

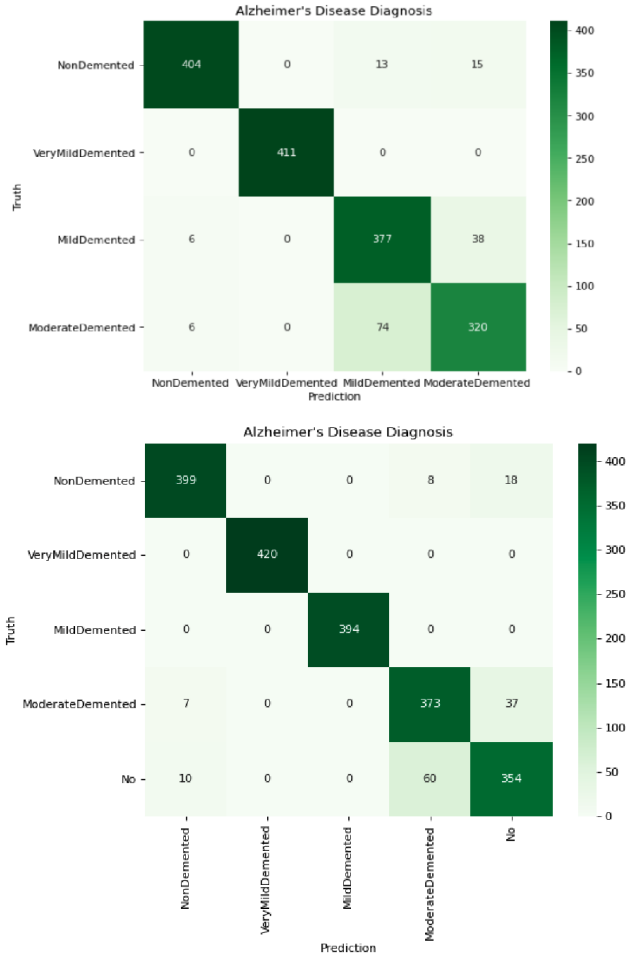

Fig. 7. Confusion Matrices generated for (a) BatchConfig-4a and (b) BatchConfig-4b

The loss curve tells us about the training process and direction of network learning. The loss decreases in the curve, which results in network learning. Our Sequential CNN model can achieve a maximum of 93.57% accuracy with BatchConfig-3b (6000 including CatB). From Fig. 9, shows that the Loss is decreasing; this confirms that the model is learning from the data.

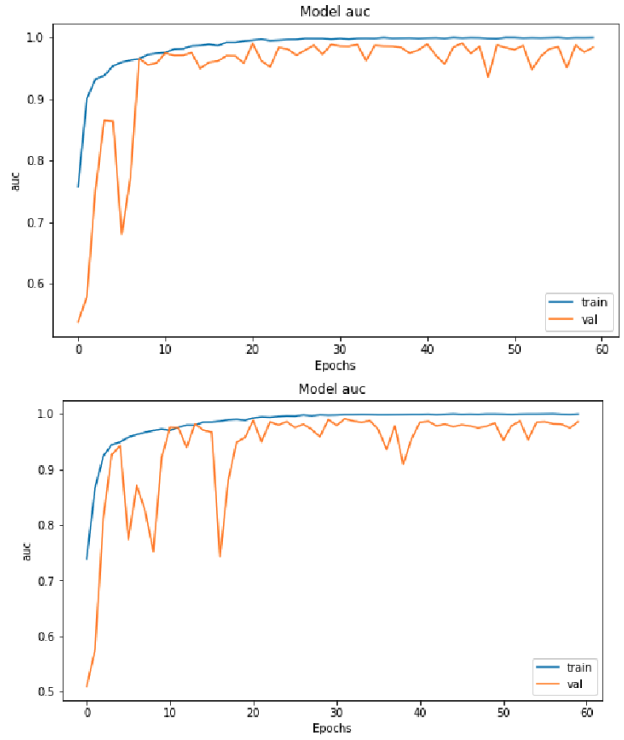

Fig. 8. AUC Curves for (a) BatchConfig-3b and (b) BatchConfig-4b

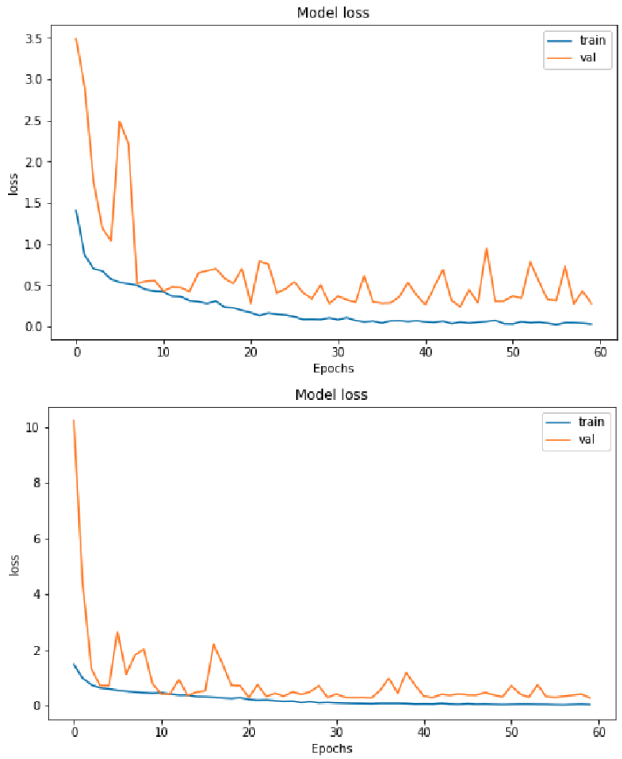

Fig. 9. Loss curves for (a) BatchConfig-3b and (b) BatchConfig-4b

V. Discussion

Based on the results obtained from the experiments performed, we can compare the results of previously investigated techniques mentioned in the Literature Survey Section. Table II summaries the various techniques with the best accuracies from each technique.

TABLE II. Comparison Of Best Accuracies Obtained From Various Techiniques

Approach	Technique	Modalities	Classification	Accuracy (%)
Fan *et al.* [8]	SVM	MRI	4-way (AD/MCI/LMCI/ NC)	99.27
Liu *et al.* [9]	WBHN	MRI	2-way (AD/HC)	94.65
Rao *et al.* [10]	SLR	MRI	2-way (AD/NC)	85.26 ± 1.39
Tong Tong *et al.* [11]	NLGF	MRI, PET, CSF, Genetic	2-way (AD/NC)	91.8
O. Ben Ahmed *et al.* [12]	Hippo VF (CHF) + CSF	MRI	2-way (AD/NC)	87.0
A. Farooq *et al.* [13]	GoogLeNet	MRI	4-way (AD/MCI/LMCI/ NC)	98.88
Proposed	**Deep CNN-based**	**MRI**	**5-way**	**93.57**

From Table II, we can observe that Fan *et al.* using Support Vector Machines (SVM) were able to obtain an accuracy of 99.27% over a 4-way classification, in the best-case test sets. However, the accuracy falls to 55.42% in the worst-case test sets [8]. Liu *et al.* using Whole Brain Hierarchical Network (WBHN) were able to obtain an accuracy of 94.65% over a 2-way classification using the ADNI dataset [14].

Rao *et al.* using Sparse Logistic Regression (SLR) were able to obtain an accuracy of 85.26 ± 1.39% over a 2-way classification using only the ADNI dataset. Tong Tong *et al.* using Non-Linear Graph Fusion (NLGF) were able to obtain an accuracy of 91.8% over a 2-way classification while using MRI, PET, CSF, and Genetic Modalities.

O. Ben Ahmed *et al.* using Hippocampal Visual Features (Circular Harmonic Functions) + Cerebrospinal Fluid (Hippo VF (CHF) + CSF) were able to obtain an accuracy of 87% over a 2-way classification using only the ADNI dataset. A. Farooq *et al.* using GoogleNet were able to obtain an accuracy of 98.88% over 4-way classification using the same dataset.

In this paper, Deep CNN was studied producing an accuracy of 93.57% over a 5-way classification while combining ADNI dataset and healthy brain MRI dataset [15].

VI. Conclusions

In this paper, Sequential Deep Convolutional Neural Networks was used to first perform a 5-way classification on brain MRI images of ModerateDemented, MildDemented, VeryMildDemented, NonDemented, and Healthy over multiple dataset batch sizes, which produced an accuracy of 93.57%. The 5-way classification accuracy chart (Fig. 5) was compared with the prior 4-way classification (excluding the CatB) accuracy chart, and it was observed that there was a significant improvement in the classification accuracy. It shows that Deep CNNs have a solid ability to classify brain MRI images with sufficient accuracy without any explicit feature selection.

This study can be further extended to allow reinforcement learning by taking the physician's final report on the patient and automatically augmenting the model without retraining it. It saves much computational time as retraining the model is time-consuming. Achieving this will help physicians on-field and reduce the time between first symptoms and begin of treatment which can significantly improve the survivability of a patient. Another dimension that can be explored is the use of the Deep CNN for other diseases as well and comparing other methods' accuracies and performances.

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