IIETA International Information and Engineering Technology Association
Advancing the World of Information and Engineering

Traitement du Signal
Vol. 41, No. 4, August, 2024, pp. 2177-2183
Journal homepage: http://iieta.org/journals/ts

Improving Efficiency in Prediction of Dementia Using Deep Learning Technique

Priya Vijay[1*], Monisha Sarangan[2]

[1] Department of Information Technology, Rajalakshmi Engineering College, Kancheepuram 602105, India
[2] Data Science, Rajalakshmi Engineering College, Kancheepuram 602105, India

Corresponding Author Email: priya.vijay@rajalakshmi.edu.in

https://doi.org/10.18280/ts.410446

Received: 24 July 2023
Revised: 21 November 2023
Accepted: 8 March 2024
Available online: 31 August 2024

Keywords:
dementia, CNN, deep learning, patients, disorder, early detection of Alzheimer

ABSTRACT

Deep learning algorithms are thought to be effective tools for diagnosing cerebrovascular disorders. On the one hand, memory loss, impaired reasoning, behavioral changes, and impaired ability to do daily chores are all hallmarks of dementia. Our goal in developing this deep learning model was to be able to predict when Alzheimer's disease will manifest in its early stages. The mono objective and multi objective classification and feature selection processes used evolutionary algorithms to aid in the natural selection process. Common algorithms that are used in this proposed work is the convolutional neural network (CNN). To counteract the variables that cause dementia, the proposed method combines information from written descriptions of the condition with pictures of both healthy and diseased brains. Neuroimaging research have shown that deep learning algorithm CNN are effective at differentiating between dementia and a healthy ageing brain with 98% accuracy. A sort of artificial intelligence that mimics the brain is known as neural networks. They can spot patterns, learn new ones, and forecast the future using data.

1. INTRODUCTION

Dementia [1, 2] is a disorder defined by a cluster of symptoms that impact daily functioning and can develop as a result of brain damage from disease or trauma. Memory, cognition, and behavior all gradually deteriorate as a result of the symptoms, which severely impact the sufferer's capacity to live a normal life. Dementia is defined by a gradual and severe decline in cognitive functions such as learning, memory, and thinking. Dementia, which can manifest in a variety of ways, is far from a natural aspect of becoming older; still, it impacts millions of people and becomes more prevalent with age (about one-third of those aged 85 and up may have dementia). Dementia progresses through seven identifiable stages, and the cognitive decline associated with dementia does not happen suddenly. The prevalence of Alzheimer's disease [3, 4] is high. Dementias like Alzheimer's begin with the dysfunction and eventual death of neurons, which are brain cells. Dementia patients experience an outsized loss of neurons compared to the general population as they age. Treatment may alleviate symptoms of certain diseases that mimic dementias, especially those caused by drug interactions or vitamin deficiencies.

It is now popular to use deep learning approaches that are based on feature selection, a type of data processing meant to supplement the built-in model selection procedure of conventional Deep Learning (DL) [5] methods. Every DL algorithm is known to have a method for choosing the best model from an ideal set of input features. The computational component of AI, uses data mining, pattern recognition, and knowledge discovery to automatically learn from data and create predicted task flows. Traditional artificial intelligence uses variables like (predictor and target variables) method. The training method attempts to discover a collection of model parameters that maximizes the association between the predictor (input characteristics) [6, 7] and the target variables by means of a looping procedure. The trained model employs the after receiving new input data, an established pattern can be used to estimate the target variable for the predictive factors. Patterns used in deep learning require at least two processors usually local computing settings, such as personal computers or cloud computing and corporate data centers. Prior to sending our data to an ML method, we make enormous efforts to alter them using simple linear correlation, or principal component analysis (PCA) analysis [8, 9]. Several experts automate the progression of the restrictions of the existing DL methods by using unusual approximations data to an DL method, we make enormous efforts to alter them using simple linear correlation, or principal component analysis (PCA) analysis. Several experts automate the progression of the restrictions of the existing DL methods by using unusual approximations. DL calculations are based on a difficult ML plan that is not exactly a match for the regular work method. We appear to have miscalculated the ML estimations since, for the most 8 parts, we ignore the subtleties of how objects go together and instead use them ready to move. HML is a development in machine learning that flawlessly combines several computations, methods, or procedures from comparable or dissimilar data spaces or use areas with the intention of improving one another.

No single DL [10] approach is suitable for all problems, just as no single cap fits all heads. Similar to how not one cap fits all heads, no singular ML approach is appropriate for all problems. When dealing with complex input spaces with multiple layers, some methods that perform well when dealing with noisy data may not be as effective. Others might not be the same as them. Due to the limitless possibilities for the hybridization of traditional DL approaches, everyone should be able to gather innovative combination models in a variety of ways. Various DL [11, 12] algorithms like CNN, RNN are used in recent times to predict various diseases to improve accuracy rather than ML algorithms.

An estimated 10 million new instances of dementia are reported annually, impacting over 50 million people [13] globally. The condition will be tripled by 20250 [14] which becomes very crucial problem among aged people. Using training and test data fed into a Convolutional Neural Network (CNN) Model, it is possible to identify people with mild dementia, moderate dementia, and severe dementia. The effort aims to diagnose Dementia early by utilizing MRI brain scan images for training with deep learning algorithms and then comparing the properties of demented brains to those of healthy brains to see if the former can more accurately predict illness.

2. RELATED WORKS

A publication titled "Dementia Prediction Support Model Using Regression Analysis and Image Style Transfer" is slated for release in 2022 by Baek and Chung [15]. The aforementioned article is useful for locating the specifics of a study that contrasted the outcomes of picture transmission at various sickness stages. Brain damage caused by dementia, alcoholism, and cerebral haemorrhage are remarkably similar.

Dashwood et al. [1] published "Artificial intelligence as an aid to diagnosing dementia: an overview" in 2021. The present research compiles AI-based dementia diagnostic tools. Some examples of these applications include genetics, neuroimaging, medical records, augmented reality, and language analysis (both written and spoken).

According to Fernando Garcia-Gutierrez and Alfonso Delgado-Alvarez, "Diagnosis of Alzheimer's disease [16-19] and behavioural variant frontotemporal dementia with machine learning-aided neuropsychological assessment using feature engineering and genetic algorithms" should be implemented in 2021. Building AI models for cognitive evaluation and diagnosis is the main focus of this research. Feature selection and classification were among the many single- and multi-objective tasks that evolutionary algorithms based on natural selection were employed for. In addition to the meta-model approach, more conventional methods like Support Vector Machines and Naive Bayes were also employed.

Bron et al. [20] highlight that estimating clinical state, predicting outcomes, and monitoring progress in (pre-clinical) dementia are all integral components of Oxtoby d's proposed "Neurogeome" study.

According to the study [21], there is a "strong movement in clinical research advocating for a more personalised approach in medicine, using more advanced analytical approaches." In their discussion of machine learning methods for dementia prediction using the Oasis dataset, Gupta et al. [22] found that the deep learning Ludwig classifier outperformed the random forest algorithm by a significant margin (95% vs. 85%).

The members Rossini et al. [23] discussed various forms of AD and retrieving features for Mil Cognitive Impairment with the help of graphic analysis tools. The did analysis with help of machine learning techniques and determined brain aging connected networks through electroencephalographic data.

It was written by James et al. [24] in their study in the titled "Deep learning-based brain age prediction in normal aging and dementia," suggested a model that uses machine le to forecast brain age from a big dataset of structural MRI and fluorodeoxyglucose positron emission tomography studies. Next the model was examined to determine if the age difference in the brain was associated with degenerative diseases such as Alzheimer's disease, frontotemporal dementia, moderate cognitive impairment, and Lewy body dementia.

Song et al. [25] portrayed on how diabetes can affect and be one of the feature for AD. Basheer et al. [26] developed a CNN model for Oasis Dataset with varying features and optimization techniques to increase the accuracy higher than the state of art papers compared and achieved 92% accuracy.

Data used to feed different models [27-29], including demographics, medical history, cognitive tests, neuroimaging, and functional evaluations, is often collected in showcased clinical contexts.

Li and Fan [30] did one year follow up for the MRI images and studied hippocampal MRI images to predict the cognitive impairment status development through Deep recurrent neural networks. The work showcased longitudinal data provide more accuracy and best suited for RNN models than cross sectional data given in the data set [31].

Challenges and issues:

The related works pave a way with the following challenges and issues that need to be addressed to predict dementia.

Overfitting error: As the images in the training data set are large in number, the error rate showed in graph will be less in difference while the error rate in testing data and the validation data might be higher because the images in test data will be less in number so that the model faces overfitting in the graph.

Scale Difference: In the image classification models, the images will be in various sizes due to the image taken from various sources because of this issue the model faces scale variation error. Prediction accuracy might affect due to this scale differences.

View point variation: This is the type of error which occurs when the dimension of the image changes like it is rotated or tilted. The brain image that is captured will have various dimensions which leads to view point variation when the data is put into the training model.

Illumination: Convolutional neural networks should be able to detect image features and deal with pixel variance, even though picture intensities could differ. Despite the different brightness levels in the images, our model has to assign them to the same label.

Background Clutter: The semantic understanding of the image should be enhanced in the model, the image might contain noise, our model has to eliminate the noise and capture the right features. The clear dimensions of the image will be good enough to get the features and the noise should get eliminated in the preprocessing module to avoid clutter errors.

Intra-Class Variation: Some of the images which belong to same class have slight variations which will be partially from class A and class B, this is called intra-class variations in convolution neural networks, this will affect the accuracy of the model. To avoid this kind of error in the model, it is better to have categorical data set.

Feature retrieval: Convolutional Neural Network captures lots of features from an image, so when the validation image is given to the model, the feature retrieval takes some time classify the image with respect to its right class. At that time, the feature of the image is extracted from the memory it may take a while to classify the image according to its respective feature. The compile time may exceed in seconds due to this feature retrieval process.

The proposed method uses GoogleNet Convolutional Neural Network deep learning algorithm with ReLU Activation function to address the above challenges and issues articulated form survey.

3. METHODOLOGY

The proposed system for detection of Dementia comes under the traditional image classification methods and the images are classified using the Deep Learning Technique [31], to be specific – Convolutional Neural Network is used to classify the images according to its classes.

Dementia detection approaches utilise convolutional neural networks, an essential part of Deep Learning. The model's procedure begins with collecting relevant data. After collecting a large quantity of MRI scan images, the following step is to divide the data into two sets: one for training and one for testing. It all starts with feeding the algorithm the pictures from the training dataset. The outcomes of the test set and training set are already known to us. The model is provided with the test data once it has retrieved features from the training data set. We can now see the metrics; accuracy and loss are the most crucial ones. Once the accuracy and loss are taken, we must train the model in such a way that it gives higher amount of accuracy, this can be done by changing the values in the hyper parameter where the model is trained. The model is now ready for validation, using the validation data set the model can be tested. The outcome is taken by feeding the validation data into the system.

The algorithm for the proposed model is given below in Figure 1.

The architecture diagram for GoogleNet CNN model is shown in Figure 2.

Step 1	Initialize MRI images for prediction of Dementia
Step 2	Apply preprocessing technique to remove noise. The image size is set to 64X64.The data was normalized from [0-255] to [0-1].
Step 3	Predict the opt feature set with data exploration and visualization technique
Step 4	GoogleNet CNN model was set with hyperparameters 3 X 3 Filter size, One input layer, 3 hidden layers and one output layer with Relu activation function
Step 4	The training set and testing was with 70-30 rule.
Step 5	Evaluate the model

Figure 1. Algorithm for proposed model

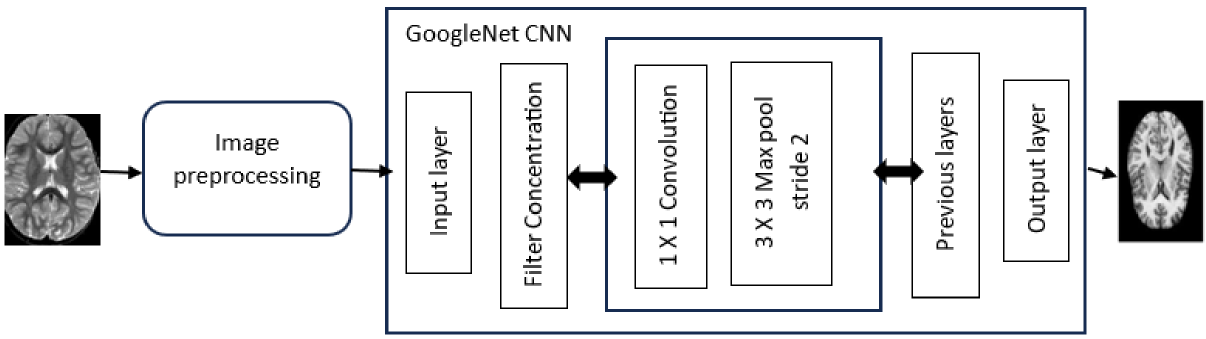

Figure 2. Proposed CNN architecture

Table 1. Dataset information

Dataset Type	Dataset Characteristics	Attribute Characteristic	Attributes	SPLIT	
				TRAIN	TEST
MRI Scan	Binary	Acquired by Model	5028	**4000**	**1028**

3.1 Data set

Biological MRI scans from both dementia and non-dementia patients are included in this dataset. The primary goal of the knowledge is to differentiate between healthy and Demented individuals mistreating the features, which is about zero for "healthy" and one for “Demented” people. The data The knowledge is in computational model of CNN. This dataset has the record of 5028 images of MRI scans, out of which 3200 patients have Dementia disorder, The dataset information is given below as Table 1.

A number of characteristics were retrieved, similarly because the model will acquire the features of the MRI images by itself, the added advantage in using the convolutional neural network is the features need not be given to the system manually instead the training happens by reading and acquiring the characteristics in the image of binary class. In the training of the specified model, the dataset is differentiated into two classes, one is demented and the other one is healthy.

3.2 Data preprocessing

All the images in the training set are modified, but not the images in the test set, in order to avoid overfitting. The sole method to stop CNN from overfitting is to apply transformations to the images, which are nothing more complicated than simple geometrical transformations, zooms, or rotations. Therefore, to shift certain pixels, rotate the photos slightly, flip them horizontally, and zoom in and out, images are generally applied with some geometric changes. Many adjustments will actually be made to the pictures in order to enhance and modify them; this procedure is called image augmentation. .In reality, it involves adjusting the images in the training set to avoid overlearning in our CNN model. The images to the size target of (64, 64) is resized to (224,224), whether it was for the training set or test set since the GoogleNet CNN input size is set as (224,224) which will be compressed to 64 size output channel.

After Data preprocessing data exploration is done. Univariate graphical approach is applied to find out distribution's form and all of the data values are displayed in stem-and-leaf plots.

The object of the image is produced when each pixel takes a value between 0 and 255, which is particularly required for neural networks. The tool that does all the transformations to the training set's photos is represented by the Data Generator class named train datagen. For instance, the rescale parameter divides each pixel's value by 255 to apply feature scaling, while the subsequent changes amplify the images on the training set. Next, the train_datagen object is connected to the training set by importing it. Then traditional batch size 32 is selected to batch the photographs in each layer.

3.3 Building CNN

The following hyperparameters are set for CNN to predict dementia with highest prediction accuracy.

Three hidden layers are set up in one input layer, one output layer, and a 3 × 3 filter size is selected. The number of rows and the number of columns match the kernel size of the feature detector precisely. ReLU parameter is employed as activation function since it relates to rectifier activation. Max Pool is selected using a 3 × 3 pool size and stride 2 with 1 × 1 convolution layers in-between the max pool layers. The output of several pooling layers is flattened and pooled to produce a single-dimensional vector. An average pooling layer is created on top of that flattened layer instead of fully connected layer, and the input to the neural network will be a simple one-dimensional vector. CNN was trained with 25 epochs. With a factor of 10 applied per 5 epochs, the learning rate was set to 0.01.

4. RESULT AND DISCUSSION

Methods for Data Preprocessing The training and testing datasets undergo data wrangling and cleaning in order to make them suitable for use with the CNN model. The result obtained before applying preprocessing technique is as shown below in Table 2.

Figure 3 shows the sample output generated after executing the GoogleNet CNN model on the input picture, which is applied after preprocessing.

Table 2. Evaluation matrices for CNN before applying preprocessing techniques

Accuracy	Precision	Recall	F1	Roc
0.94	0.93	0.81	0.92	0.90

```
Model: "CNN"

Layer (type)                 Output Shape              Param #
==============================================================
input_1 (InputLayer)         [(None, 224, 224, 3)]     0

conv2d (Conv2D)              (None, 112, 112, 64)      9472

max_pooling2d (MaxPooling2   (None, 56, 56, 64)        0
D)

conv2d_2 (Conv2D)            (None, 56, 56, 64)        4160      [

conv2d_4 (Conv2D)            (None, 56, 56, 32)        2080      [

max_pooling2d_1 (MaxPoolin   (None, 56, 56, 64)        0
```

Figure 3. Output of GoogleNet CNN

These datasets have already been processed, dividing them into distinct training and testing sets. Training purposes account for 70% of the data. For optimal precision, 30% of data is used in testing. To identify "Demented people" and "Non demented" individuals, a Convolution Neural Network extracts features from brain scans and uses them in a binary classification system. Figure 4 below shows the demented and non-demented images.

Demented image Non demented image

Figure 4. Prediction of dementia

A confusion matrix with values was used to assess the outcome. For a model to be considered true positive (TP), it must accurately predict that the patient has illness. When the model accurately predicts that the patient does not have disease, it is called a true negative (TN). The term "False Negative" (FN) refers to an incorrect negative class prediction, while "False Positive" (FP) describes an inaccurate positive class prediction (patients without disease labelled as negative). You may find the confusion matrix in Table 3.

Table 3. Confusion matrix for proposed data set

		Actual Values	
		0	**1**
Predicted Values	**0**	True Negative (TN) Patient not having disease	False Positive (FP) Patients not having disease predicted True
	1	False Negative (FN) Patients having disease predicted False	True Positive (TP) Patient having disease

A Heat map was generated to do corellation analysis with following parameters.

The model's predictions of the positive class—the patient's illness—are called True Positives (TP). A True Negative (TN) patient is one for whom the model accurately predicted the absence of illness. The "false positive" (FP) is shorthand for a positive class that is mistakenly predicted. An incorrectly negative categorization prediction is called a "False Negative" (FN).

One way to visually represent the relationships between variables is with a correlation heat map, which is essentially a correlation matrix. Any number between -1 and 1 could represent the correlation in this heat map. You can see the heat map in Figure 5.

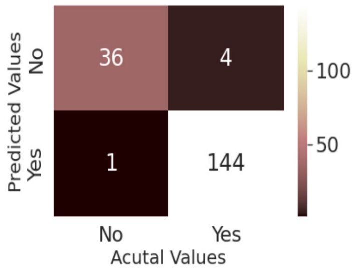

Figure 5. Heat map for confusion matrix

Out of 185 recordings, 37 "Yes" and 144 "No" Predictions were made, as seen in the third figure above.

True Negative: 36 out of 36 occasions, the dementia prediction was accurate. A 144/144 True Positive rate indicates that the model was correct in predicting that the patient had the illness.

False Negative - On one occasion, while the patient was actually sick, the model incorrectly predicted that they were not sick.

A false positive occurs when the model incorrectly predicts that a patient has a condition four times when in fact the patient does not have the disease.

A google net framework was used to implement CNN to avoid overfitting.

The below Table 4 shows the evaluation metrices for the proposed model.

Table 4. Evaluation matrices for GoogleNet CNN

Accuracy	Precision	Recall	F1	Roc
0.98	0.97	0.75	0.96	0.99

The table shows the proposed model has 98% accuracy in predicting dementia. The accuracy graph for both testing and training set is shown in Figure 6 below.

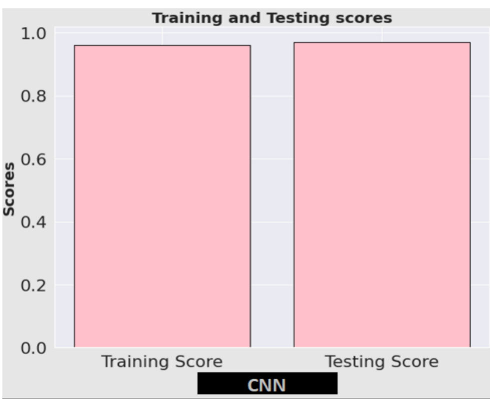

Figure 6. Training and testing set accuracy for CNN model

Table 5. Comparison of performance metrics on varying epochs

Epoch	Accuracy	Precision	Recall	F-Measure
5	0.65	0.69	0.55	0.69
10	0.75	0.77	0.65	0.79
15	0.82	0.85	0.79	0.80
20	0.92	0.93	0.80	0.90
25	0.98	0.97	0.75	0.96

The accuracy of various epochs was compared and the best output is achieved while setting 25 epochs with learning rate of 0.01 after which overfitting occurs. Table 5 compares performance indicators over different epochs.

The result was also compared for various CNN architecture models like AlexNet, VGG16 and GoogLeNet models. The comparison of accuracy is shown in Figure 7.

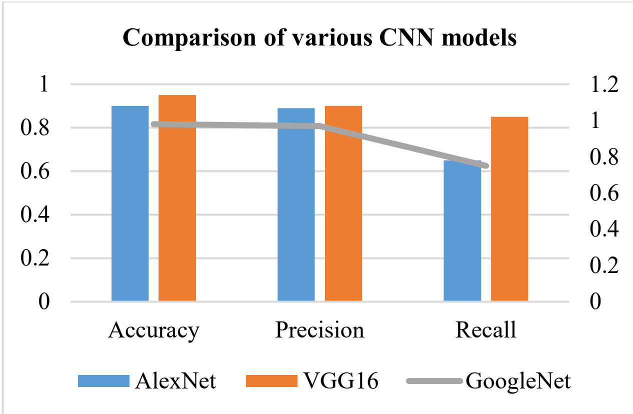

Figure 7. Comparison of various CNN models

5. CONCLUSIONS

Separation of the MRI images of brain into binary classes is a crucial step in the analysis. The output and the implementation of the overall process are shown with relevant datasets, processing details and suitable plots. The dataset containing the mixture of Demented and Non demented images are well trained into the Convolutional Neural Network, thus in the validation module our system is able to accurately judge whether the patient is suffering from Dementia or the patient is healthy. This convolution Neural network model is trained with 98% accuracy. The paper concludes the best accuracy was achieved on using GoogleNet CNN architecture rather than other CNN models. In future, the model shall be trained with even more accuracy to predict the results and the model to predict the accuracy with minimum optimal time.

ACKNOWLEDGMENT

This work is supported by the Centre of Excellence Data Science of Rajalakshmi Engineering College.

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