Detecting Alzheimer's Disease Using Machine Learning Methods

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Abstract. As the world is experiencing population growth, the portion of the older people, aged 65 and above, is also growing at a faster rate. As a result, the dementia with Alzheimer's disease is expected to increase rapidly in the next few years. Currently, healthcare systems require an accurate detection of the disease for its treatment and prevention. Therefore, it has become essential to develop a framework for early detection of Alzheimer's disease to avoid complications. To this end, a novel framework, based on machine-learning (ML) and deep-learning (DL) methods, is proposed to detect Alzheimer's disease. In particular, the performance of different ML and DL algorithms has been evaluated against their detection accuracy. The experimental results state that bidirectional long short-term memory (BiLSTM) outperforms the ML methods with a detection accuracy of 91.28%. Furthermore, the comparison with the state-of-the-art indicates the superiority of the our framework over the other proposed approaches in the literature.

Keywords: Machine learning · Deep learning · Detecting Alzheimer

1 Introduction

Alzheimer is from a family of diseases that can develop dementia, specially in elderly people. Dementia is a loss of memory and/or other mental disability that can cause physical damaged to the brain. Although Alzheimer is the most common type of dementia but there are different types of dementia [35,49], such as vascular dementia, Lewy Body disease, frontotemporal dementia, alcohol related dementia and HIV associated dementia, *etc.*. The most common type of dementia after Alzheimer's disease is vascular dementia which can happens after stroke. In addition, some of the causes of dementia are reversible such as thyroid problem and vitamin deficiencies. The dementia is not just a disease but its

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associated risks such as decline in the memory significantly reduces a person's ability to perform daily tasks. It is expected that the number of people affected from dementia will increase over the time. The early detection can not only help doctors to precisely make decision on the treatment but also help preventing the complications [21]. It is important to develop a system that can help in early detection of dementia.

The Alzheimer's disease has number of symptoms, especially in the elderly people that can cause problems to perform daily tasks due to memory loss. Although the Alzheimer is not normal due to aging, its risk factor increases with the aging. Most of the people who suffer from Alzheimer are aged 65 or above. However, it not uncommon to have this disease in the people younger than 65. For instance, more than two hundred thousand American aged less than 65 suffers from Alzheimer disease. Figure 1 shows the difference between the normal brain and Alzheimer's brain [47].

It can be noticed that the brain of the Alzheimer's disease in not only significantly smaller than the normal brain but is affected severely from neurological disorder and dysfunction. Additionally, Fig. 2 presents some of the common symptoms of the Alzheimer's disease. The most common types of symptoms are loss of memory, changes in the behaviour, difficulty with everyday task and confusion in familiar environments.

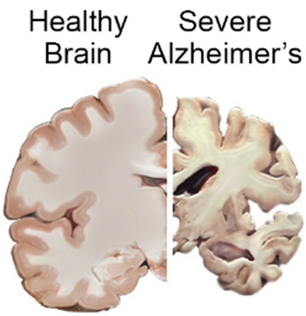

Fig. 1. Difference between a normal brain and a severe Alzheimer's brain [47].

Practically, no effective cure to treat Alzheimer's disease exist to date. However, there exist ways that can temporarily slow down the process of Alzheimer's symptoms and improve the quality of the life of the patient. To this end, significant research efforts are dedicated to find the effective ways of treating the Alzheimer's disease with a focus on preventing the disease from progressing over the time [39].

It is suggested that ML and DL algorithms, which have proven their significance in various fields, can help solve the problem of early detection of Alzheimer's disease clearly, ML and DL methods have their applications in

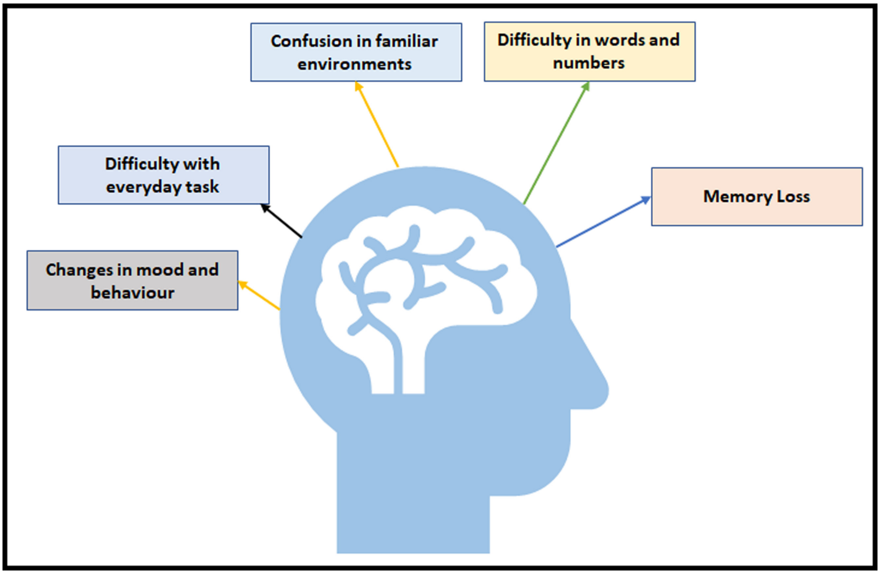

Fig. 2. Alzheimer symptoms

various domains, including but not limited to sentiment analysis [2,9–11,13–19,30,32,33], speech enhancement [27,28], cyber-security [31,34], image classification [36], energy efficiency [51], travel detection [5,6], posture detection [48], and atrial fibrillation [37,38], *etc.*. Therefore, the ML techniques including support vector machine (SVM), logistic regression, multi-layered perceptron and deep learning classifiers. In particular, feature selection is an important element of traditional ML classifiers which is inherently incorporated in DL classifiers. Generally, DL classifiers achieve better results on large datasets.

In this paper, we proposed a novel approach, based on ML and DL methods, to detect Alzheimer's disease. The obtained results from DL algorithm are compared against traditional ML algorithms [1,24–26]. In particular, bidirectional long short-term memory (BiLSTM) outperforms all the considered ML and DL methods, with a detection accuracy of 91.28%.

The rest of the paper is structured as follows. Section 2 provides the state-of-the-art in Alzheimer detection. Section 3 presents the proposed methodology. Section 4 provides the experimental results of the proposed Alzheimer detection and discussion, and finally Sect. 5 concludes the paper.

2 Related Work

In this section, we discuss the current state-of-the-art to detect dementia and Alzheimer's disease using DL and ML algorithms.

The work in [7] propose novel metrics to identify the Alzheimer's disease using pattern similarity score. The authors characterize the metrics in terms of conditional probabilities modeled by logistic regression. In addition, they explore the performance of anatomical and cognitive impairment which is used to generate the output of the classifiers using different types of data.

The authors in [41] use the online available datasets of MRI scan images and other cognitive features, such as RAVLT tests, MOCA and FDG score *etc.* to identify the Alzheimer's disease. In particular, clustering algorithms are developed based on logistic regression and SVM to detect the patient having Alzheimer's disease. Ammar et al. [4] presented a framework based on the speech processing to detect dementia. The framework was used to extract features from patients with dementia and without dementia wherein the speech data used was having verbal description and manual transcription. Therefore, the speech and textual features were used to train ML classifiers. The authors achieved an overall accuracy of 79% only.

Another interesting work in presented in [52] where authors introduced a detection method based on the MRI images of brain based on the Eigenbrain. Their approach used SVM and particle swarm optimization to train the model. Their proposal achieved satisfactory results in detecting the parts of the brain affected from Alzheimer's disease. Working on the similar lines of MRI scans, authors in [44] detected dementia and other different features using gradient boost and Artificial Neural Network (ANN) models. The authors achieved comparable results with the ones presented in [52]. The authors in [45] proposed a hybrid multimodal method based on the cognitive and linguistic features. The authors used ANN to train the model detect Alzheimer's disease and its severity. Their scheme achieved good results as compared to the state-of-the-art.

3 Methodology

This work proposes a novel Alzheimer's detection system using different ML and DL algorithms. In particular, the raw data coming from MRI scans is preprocessed before applying various ML and DL methods. Figure 3 presents an overall picture of the proposed Alzheimer detection system.

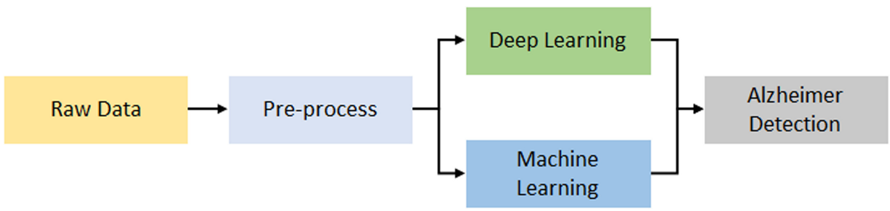

Fig. 3. Overview of Alzheimer detection framework

3.1 Machine Learning Methods

This subsection highlights our simulation settings to train different ML models. Scikit-learn is used to train ML classifiers. More specifically, radial basis function (RBF) kernel is used to train support vector machine (SVM). Elasticnet is used as a penalty for logistic regression, two hidden layers are used for multilayer perceptron (MLP), number of neighbors are set to 5 for k-nearest neighbors (KNN), epsilon is set to *float* for Naïve Bayes, max features are set to *int* for decision tree and finally number of estimate is set to 100 for random forest. It is worth mentioning that the ML classifiers are trained based on standard deviation, average, square root, skew, maximum and minimum value.

3.2 Deep Learning Methods

This subsection highlights our simulation settings to train different DL models. Mainly, two different DL models are used in this work, namely convolutional neural network (CNN) and LSTM The developed CNN architecture, inspired from [12,29,42], contains input, hidden and output layers where hidden layers are made up of convolutional, max pooling and fully connected layers. In particular, 10-layered CNN architecture is employed. On the other hand, LSTM architecture, inspired from [3,8,23,43], contains two bidirectional LSMT along with 128 and 64 cells with dropout of 0.2. In addition, a dense layer with two neurons and softmax activation is used.

4 Experimental Results and Discussions

The dataset consists of 373 images from 150 subjects aged between 60 and 96. The MRI scan of each subject was taken for his one or two visits with a separation of at least one year between visits. All the subjects were right-handed with a mixture of men and women. Out of 150, 72 subjects were non-demented, with no mental disorder or dysfunction. On the other hand, 64 subjects were categorized as demented during their initial visit, including 51 with mild to moderate Alzheimer's disease. Importantly, the dataset is marked with five labels as normal, very mild dementia, mild dementia, moderate dementia, severe dementia.

In order to detect Alzheimer's disease, we compare the results of different ML classifiers including logistic regression, SVM, random forest, MLP, KNN, naïve bayes, decision tree and DL classifiers (1D-CNN, 2D-CNN, LSTM and BiLSTM). For ML classifiers, the features, such as skew, percentile, standard deviation, mean and square root are used to train the classifier. However, for DL classifiers raw data is used to train the models. It is important to that we used 5-fold and 10-fold cross-validation to perform the experiments. The considered evaluation parameters are precision, recall, f-measure and detection accuracy. It is evident from Tables 1 highlights are results of different ML and DL methods for a 5-fold cross validation settings. It can be noted that SVM provides the most promising results as compared to other ML methods such as logistic regression,

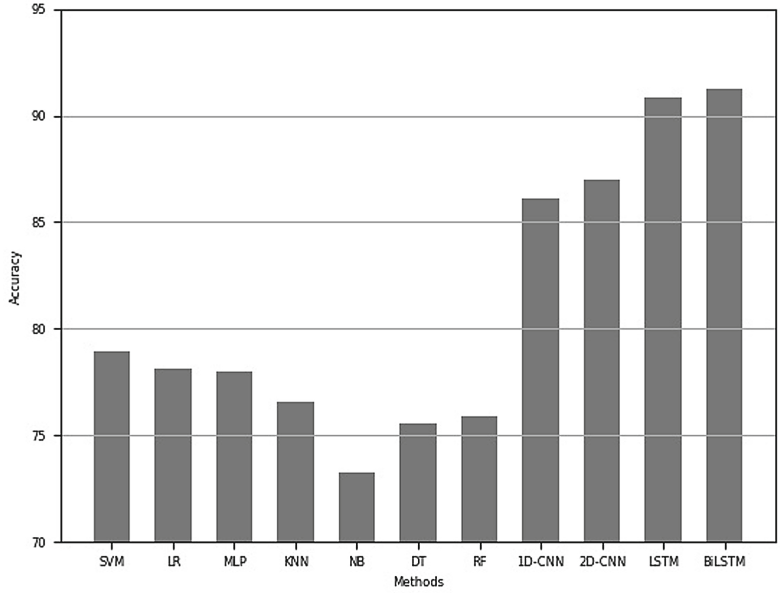

Fig. 4. 5-Fold summary of machine learning and deep learning results

MLP and *etc*. Overall, the experimental results show that the DL classifiers outperforms ML methods. However, the DL classifiers are expensive both in terms of computational resources and time.

Table 2 shows the summary of considered ML and DL results to the detect Alzheimer's disease for a 10-fold cross validation settings. Here again, SVM classifiers outperforms to other ML approaches such as logistic regression, MLP, KNN, Naive Bayes, decision tree and random forest. On the other hand, naive bayes gives the worst performance as compared to all ML and DL methods and also it took longer to train the model. Overall, DL methods perform better. In particular, BiLSTM achieved the best performance. However, BiLSTM took longer to train the model.

4.1 Discussion

It is important to note that the detection of Alzheimer's disease using ML methods is cost-effective (Computation and time) than DL algorithms. On the other hand, training deep learning classifiers is time and computationally expensive. Clearly, as shown in Figs. 4 and 5 the BiLSTM achieved better performance as compared to other methods in both 5-fold and 10-fold cross validation strategies. In addition to having such a promising results, our work has certain limitations as well (1) The dataset is very small with only 373 images in total. (2) The dataset considers people of aged 65 and above only (Table 3).

Table 1. Summary of machine learning and deep learning methods to detect Alzheimer using 5-fold cross-validation

Methods	Training accuracy	Testing accuracy	Precision	Recall	F-Score	Time
SVM	80.78	78.56	0.78	0.76	0.76	2 m 21 s
Logistic Regression	80.23	78.12	0.78	0.77	0.78	2 m 8 s
MLP	79.81	78	0.78	0.77	0.78	2 m 6 s
KNN	77.25	76.58	0.76	0.75	0.76	2 m 2 s
Naive Bayes	75.89	73.28	0.73	0.72	0.73	2 m 19 s
Decision Tree	76.98	75.59	0.75	0.74	0.75	2 m 11 s
Random Forest	76.85	75.89	0.75	0.75	0.75	2 m 31 s
1D-CNN	88.59	86.14	0.86	0.85	0.86	8 m 28 s
2D-CNN	89.45	87	0.87	0.86	0.87	9 m 1 s
LSTM	91.26	90.85	0.90	0.90	0.90	10 m 17 s
BiLSTM	93.21	91.28	0.91	0.91	0.91	10 m 12 s

Table 2. Summary of machine learning and deep learning methods to detect Alzheimer using 10-fold cross-validation

Methods	Training accuracy	Testing accuracy	Precision	Recall	F-Score	Time
SVM	82.24	80.75	0.80	0.79	0.80	2 m 33 s
Logisitc Regression	81.86	79.86	0.79	0.78	0.79	2 m 12 s
MLP	80.36	79.56	0.79	0.79	0.79	2 m 31 s
KNN	78.91	76.12	0.76	0.75	0.76	2 m 4 s
Naive Bayes	75.2	71.64	0.71	0.70	0.71	3 m
Decision Tree	78.69	75.9	0.75	0.74	0.75	2 m 19 s
Random Forest	75.97	73.29	0.73	0.72	0.73	2 m 8 s
1D-CNN	88.91	86.54	0.86	0.85	0.86	8 m 5 s
2D-CNN	89.43	87.01	0.87	0.86	0.87	8 m 29 s
LSTM	93.19	91.19	0.91	0.91	0.91	8 m 45 s
BiLSTM	95.59	93.19	0.93	0.93	0.93	9 m 16 s

Table 3. Comparison with state-of-the-art approach

Ref.	Accuracy	Precision	Recall	F-Score
Zhang et al. [52]	86.24	0.85	0.83	0.84
Dyrba et al. [20]	70.4	0.70	0.70	0.70
Escudero et al. [22]	79.1	0.78	0.76	0.75
Trambaiolli et al.[50]	75.56	0.75	0.73	0.71
Liu et al. [40]	84.40	0.84	0.82	0.82
Shankar et al. [46]	76.23	0.75	0.74	0.75
Our Approach	93.19	0.93	0.93	0.93

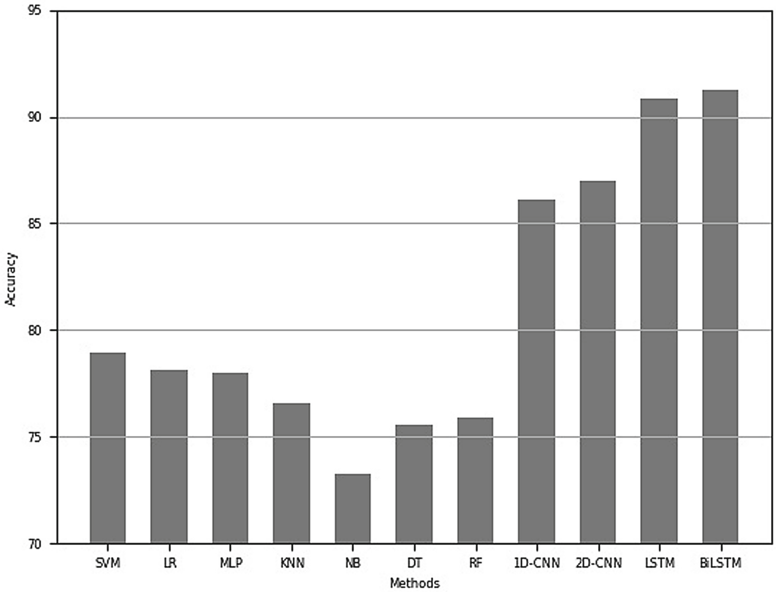

Fig. 5. 5-Fold summary of machine learning and deep learning results

5 Conclusion

The alzheimer's disease is the most challenging health problems scientists are facing since decades. In this paper, we present a novel framework based on the ML and DL algorithms including SVM, logistic regression, MLP, KNN, Naive Bayes, decision tree and random forest, 1D-CNN, 2D,CNN, LSTM and BiLSTM to automatically detect Alzheimer's disease. The extensive experimental results show that BiLSTM achieved better performance as compared to other ML and DL algorithms. As a future work, we intend to use transformers to detect Alzheimer's disease using images, visual and acoustic features.

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