Performance Of Machine Learning Models To Predict Onset Of Dementia

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ABSTRACT

One of the most common causes of dementia among the elderly is Alzheimer's disease (AD). Large-scale metabolic disorders like Alzheimer's and Diabetes are of great interest to researchers today because of the potential for machine learning to help identify them. The pace at which they are appearing is rising dramatically. In dementia the brain does neurodegenerative alterations. The prevalence of illnesses that impair cognition and psychological function is expected to rise in tandem with the world's aging population. The social, monetary, and economic repercussions of this will be significant. It is difficult to anticipate the course of Alzheimer's disease in its earliest stages. Treatment of AD at an early stage is more effective and has fewer side effects than treatment of the disease at a later stage. Machine learning algorithms could be used as the basis for decision-making by diagnosing any disease which aids to enhance clinical practice. In this paper we presented a model with which we can differentiate demented and non-demented people with the help of various machine learning algorithms. This plays a vital role in predicting other non-reversible diseases like Alzheimer's at their early stages.

Keywords: Machine learning, Dementia, healthcare, feature selection, prediction, data analyzing
DOI Number: 10.48047/nq.2022.20.19.NQ99107 **NeuroQuantology2022;20(19): 1161-1167**

INTRODUCTION

Major groups of symptoms like affecting memory, thinking and social abilities that are able to interfere with your daily life, are present in dementia. Dementia in itself is not a specific disease but it is caused by some other diseases. Dementia is the process part of the neurological condition that leads to a short-term loss of memory. The paranoia and the different ideas like delusions are based on the effects of stress. Damage to or loss of nerve cells and their connections in the brain are the major cause of dementia. Based upon the damaged area of the brain, dementia causes different symptoms in people. So the commonalities like deposition of protein and the affected brain area can make groups for dementia. Some common cognitive and psychological changes are seen in people with dementia as a sign or symptom to it. Dementia patients lose the capacity to speak, [9] adjust to their surroundings, and ultimately move about. They have time to find the words to express how they feel. As people's memory and cognitive abilities deteriorate, they may need extensive help to carry out even the most basic of tasks. At this point, people may need help with:

- Personal care and everyday tasks, which may need support around-the-clock.
- They have no awareness of their current location or their previous past.
- Your physical capabilities, including your ability to walk, sit, and, ultimately, swallow, may vary as you get older.
- Interpersonal interaction is becoming harder.
- An increase in the frequency of infectious diseases, including pneumonia.

Differentiating between the demented people and non-demented people:

Alzheimer's disease is common dementia and it is affecting people more than in the world like 46 million. It is a multifactorial disease that is

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Relevant conflicts of interest/financial disclosures: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest

categorized by the decline and the part which is a unique process of neuropathy. The microscopic process changes every stage of the disease. There are two main parts which are the degenerative process. The latest process in the advanced laboratory is the effective part which is monitoring the progression process in AD. The brain is affected by the individual part which is corrected by the structural aspect and the functional aspect of the section. The pattern of the distribution factor is determined by the "plaques" and the "tangles" that are reported on the same part in the AD patient and the NDAN patient.

There are some types of dementia when the condition progresses and aren't reversible namely: Alzheimer's disease, Lewy body dementia, Vascular dementia, Frontotemporal dementia, and Mixed dementia.

In this paper we discussed more about Alzheimer's disease, as it is the most common cause of a progressive dementia in older adults, but there are a number of other causes of dementia. The symptoms of Alzheimer's disease tend to Lon around for a long as the disease advances. Depending on the cause, some dementia symptoms might be reversible. This AD has no proper treatment. Alzheimer's disease (AD) is a degenerative neurological ailment that causes short-term memory loss, psychosis, and delusional thinking, all of which are often ascribed to stress or old age. Roughly 5.1% of the US population suffers from this condition [1]. Unfortunately, there is presently no effective drug treatment for Alzheimer's disease. Alzheimer's disease medication must be taken on a consistent basis for it to be effective. Due to the chronic nature of AD (1), its effects may last for decades or even a lifetime [2]. Because of this, timing the administration of medication is critical in avoiding permanent brain damage. Early diagnosis of this condition is time-consuming and costly due to the necessity for extensive data collection, the use of complex algorithms for prediction, and the involvement of a qualified medical professional [3]. When compared to human judgment, automated systems are more accurate and less prone to errors, making them a viable option for use in medical decision support systems [4]. To better understand Alzheimer's disease (AD), researchers have employed magnetic resonance imaging (MRI), biomarkers(chemicals, blood flow), and quantitative data from MRI images [5]. It helped them determine whether someone had dementia. By eliminating the requirement for human interaction, as well as saving time, the process of diagnosing Alzheimer's disease may be automated [6]. Automation not only increases productivity and reduces expenses, but it also improves accuracy. For instance, we may be able to tell whether a person has dementia by analyzing their MRI and making use of diagnostic prediction algorithms. Dementia is frequent in the early stages of Alzheimer's disease [7]. We'll have a better chance of hitting our goals if we do it this way.

In this paper we evaluated the various performance of the metric which is accurate, determined the parameter of each type of model and performed the cross-validation process. The learning model is developed by the disease which affects the people. Machine learning determines the part which is developing the function and predicts the function separately. The part of evaluation measures the field of the part of the component which is defined by the recall process, precision, f-score, and accuracy.

RELATED WORKS

For the purpose of making predictions on the start of Alzheimer's disease, ML algorithms are trained to use the oasis longitudinal dataset for feature selection and extraction. This article will offer a brief overview of the many approaches [10] used to analyses brain images for the purpose of identifying neurological disorders. In this article, we discuss the results of a literature review on the issue of using ML/DL to the diagnosis of brain illnesses and then address several of the most important problems that have developed as a direct result of this application [11]. This study uncovered the most efficient method for identifying neurological diseases and might help guide the creation of new diagnostic instruments. The authors' goal, through using machine learning and deep learning systems [12], is to compile recent research on neurological disorders including Alzheimer's, brain tumors, epilepsy, and Parkinson's. In order to choose the most effective method of diagnosis, authors may search 22 of the most popular databases on brain diseases. The use of deep convolutional auto encoders for AD

data processing. We may be able to extract MRI features that stand in for cognitive symptoms and the underlying neurodegenerative process by using data-driven deconstruction of MRI pictures [13]. Then, we apply a regression and classification analysis to see how the returned features are distributed across a wide variety of permutations, and we quantify the influence of each coordinate of the auto encoder manifold on the brain [14]. It has been suggested that combining MMSE or ADAS11 scores with imaging-derived indications may improve diagnostic accuracy for AD to more than 80%. One may use a multi-layer deep neural network for binary classification [15] that are all interconnected is used. Different activation functions are used to reveal each of the concealed layers. k-fold validation is used to choose a model with the highest performance. The Lancet Commission reported that it is possible to alter 35 percent of the risk factors for developing Alzheimer's disease [16]. Lack of education, being overweight or obese, having trouble hearing, being depressed, having diabetes, not getting enough exercise, smoking, and being socially isolated are all variables that might increase these dangers [17]. No of your age, it's best to get rid of these items since they might have a negative impact on your health. Multiple studies have shown that early detection and treatment of Alzheimer's disease's modifiable risk factors might prevent or postpone 30% of cases [18] One way to estimate one's risk of acquiring Alzheimer's disease is by employing the Lifestyle for Brain Health (LIBRA) index, as proposed by the Innovative Midlife Intervention for Alzheimer's Deterrence (In-MINDD) research [19]. The three key areas of intervention for dementia suggested by the National Academy of Medicine are cognitive training, hypertension therapy, and increased physical activity [20]. Among the several forms of dementia, Alzheimer's disease is by far the most common (AD). Vad is the second most common form of AD, after Alzheimer's with Lewy bodies. Some cases of Alzheimer's have been connected to brain injuries, infections, and heavy alcohol usage. As these two forms of Alzheimer's disease often coexist in the brain and share some modifiable risk factors [21], It would be possible to prevent Alzheimer's disease by lowering modifiable vascular risk factors. They employed neuropsychological and demographic data to generate predictions of cognitive performance using four models (SVM, Decision Tree, NN, and Naive-Bayes) [22]. When missing data were represented by arithmetic means, Naive Bayes proved to be the most precise approach. Applying ADNI data cross-validation leads to strong correlations across genetic, imaging, biomarker, and neuropsychological findings. MRI pictures from the OASIS dataset are analyzed using the voxel-based morphometric method[23].

MATERIALS AND METHODS

We used the Google Colab environment in python to execute machine learning dataset with improved performance and faster speed. At first, the Dementia's dataset was imported into Google Colab for initial analysis to get started. We used the dataset called the dementia_dataset.csv which is available in Kaggle's database. [24]. After collecting the data, it was analyzed comprehensively, with a special focus on comparing and contrasting the major study components with the associated data from each visit. The MRI scans taken throughout the course of a patient's life are our primary data source for this study. Altogether, MRI data from people, aged 60 to 98, were considered for the study [25]. Repeated scans were performed on each subject. Most people are right-handed in this culture. We can see the description of data in below table:

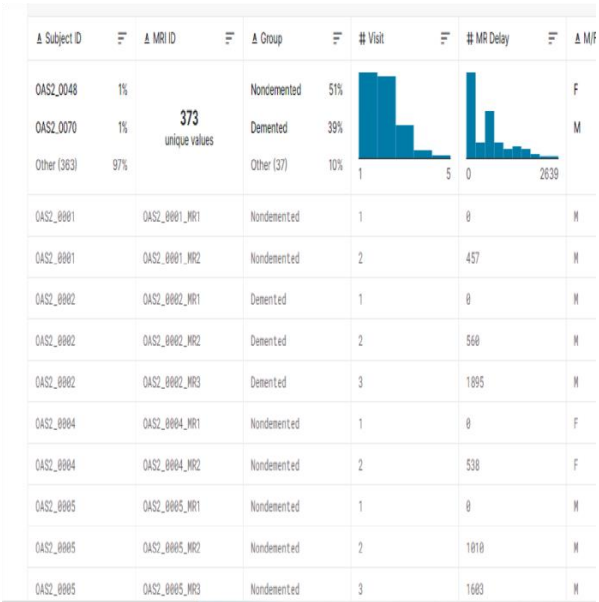

Figure 1 : Dementia data(dementia_dataset.csv)

(Source:https://www.kaggle.com/code/miteshsoni/dementia-prediction-in-depth-random-fore st/data)

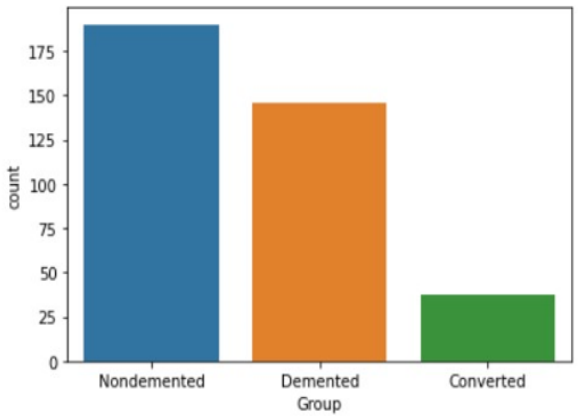

Figure 2: Data columns to decide the diseases

Figure 2 shows the group of demented, non-demented and converted groups with their count.

In order to better predict the development of Dementia, this research uses Machine Learning techniques to relevant datasets. Algorithm performance is hindered by the raw dementia datasets irregularity and redundancy [28]. Only when the data has been cleansed, normalized, and de-duplicated can machine-learning algorithm assessments begin. We can say that the "MR Delay" column has some outliers.

	Subject ID	MRI ID	Group	Visit	MR Delay	M/F	Hand	Age	EDUC	SES	MMSE	CDR	eTIV	nWBV	ASF
2	OAS2_0002	OAS2_0002_MR1	Demented	1	0	M	R	75	12	2.0	23.0	0.5	1678	0.736	1.046
3	OAS2_0002	OAS2_0002_MR2	Demented	2	560	M	R	76	12	2.0	28.0	0.5	1738	0.713	1.010
5	OAS2_0004	OAS2_0004_MR1	Nondemented	1	0	F	R	88	18	3.0	28.0	0.0	1215	0.710	1.444
6	OAS2_0004	OAS2_0004_MR2	Nondemented	2	538	F	R	90	18	3.0	27.0	0.0	1200	0.718	1.462
7	OAS2_0005	OAS2_0005_MR1	Nondemented	1	0	M	R	80	12	4.0	28.0	0.0	1689	0.712	1.039
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
367	OAS2_0185	OAS2_0185_MR1	Demented	1	0	M	R	80	16	1.0	28.0	0.5	1704	0.711	1.030
368	OAS2_0185	OAS2_0185_MR2	Demented	2	842	M	R	82	16	1.0	28.0	0.5	1693	0.694	1.037
370	OAS2_0186	OAS2_0186_MR1	Nondemented	1	0	F	R	61	13	2.0	30.0	0.0	1319	0.801	1.331
371	OAS2_0186	OAS2_0186_MR2	Nondemented	2	763	F	R	63	13	2.0	30.0	0.0	1327	0.796	1.323
372	OAS2_0186	OAS2_0186_MR3	Nondemented	3	1608	F	R	65	13	2.0	30.0	0.0	1333	0.801	1.317

297 rows × 15 columns

Figure 3 : Data after removing outliers

Figure 3 shows the data after removing the outliers that were there before pre-processing. In the process of improving performance we dropped the rows with missing values too. Also we replaced the missing values with the corresponding values, also known as 'Imputation'. Then we removed two columns named "Subject ID" and "MRI ID" because they are not impacting upon the outputs.

In the process of data cleaning we replaced demented and converted into 0 and non-demented into 1 as we can see in below figure 4:

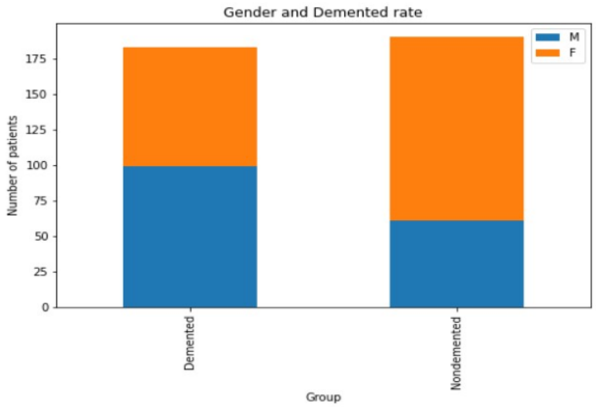

Figure 4: Demented and non-demented group analysis

With the help of the above chart we can say that men are more prone to dementia than females.

Classifier Models

Decision Tree (DT)

Decision trees are a tree-based method for regularly segmenting information depending on thresholds of features. The splitting technique allows us to build subsets by dividing instances into smaller collections. Internal nodes describe the center of a set, whereas leaf nodes describe its furthest edges. A decision tree excels when there is a strong relationship between the qualities being considered and the final outcome.

Support Vector Machine (SVM)

For this technique, we use suitable hyperplanes in a dimensional space to identify the grouping of data points. With support vector machines (25), we're trying to locate a hyperplane that divides instances of two types of variables that occupy adjacent clusters of vectors. Figure 2 shows the data decided. Closer to the hyperplane are support vectors. To use SVM, both training and test data are utilized. Target values and characteristics are separated apart from one another in training data. The model that SVM generates for predicting the test data's target values.

Random Forest (RF)

A random forest model outperforms a decision tree because it does not suffer from the

overfitting issue. The decision trees used in random forest-based models are all somewhat unique from one another. Predictions are made by the ensemble using individual decision tree models and a majority voting procedure (bagging). Therefore, each tree's predictive power is preserved while the quantity of overfitting is decreased.

Model Validation

The development of a machine-learning model requires the data to be split into training and testing sets. The next step was to get the data ready to be used in a dementia prediction model, where the training data would be put to use to construct the model. The training set was used to teach the model, and the test set was used to evaluate the accuracy of the newly learned knowledge. For the purpose of cross-validation, the dataset was divided into three sections. Predictions are made using test data, while model fit is evaluated using training and validation sets. Following cleaning and preparation, we randomly divided the data into two sets: one for training and one for testing. Applying a tried-and-true model reduces the risk of overfitting. In order to determine a model's precision, we need the ML model's training results, which are produced through Cross Validation. The task of developing a machine learning model that is devoid of background noise is not an easy one. As a result, we use Cross Validation, which entails dividing the whole dataset into n equal-sized halves. The ML model is trained at each iteration using n-1 sub-iterations. The effectiveness of the procedure is determined by averaging the outcomes of n independent trials. Ten-fold cross validation was utilized to train and test the ML model in this work.

❖ Measure the finding values of the proportion which is determined by the total number of the instance factor.

❖ The percentage of the **Accuracy** is the = [T X N + T X N / (T X P + T X N + F X P + F X N)] X 100

❖ **Precision** is measured by the number of corrective values which is positive to the rate of the divination factor which is the total values in the positive rate. The total values in the precision values are taken 1 then it is determined by the Precision = Tx P /(T X P + F X P)

❖ **Recall** is measured by the true rate for the positive part which is considered by the value is 1 and it is determined by the percentage of the recall is = T X P /(T X P + F X N)

EXPERIMENTAL RESULTS

The F1 score, together with accuracy and recall, are analyzed as effectiveness metrics. For this purpose, we use 5-fold cross-validation across four different models (Decision Tree, SVM, Random Forests, and Logistic) to determine the best parameters for each. Finally, we assess the predictive power of each model. Following model development, many measures and techniques were used to ensure that the models did not suffer from overfitting or poor parameter tuning. Performance evaluations, whether binary or multiclass, may be represented using confusion matrices. It was shown and verified that a custom-built Machine Learning classifier could identify and categorize people with dementia within a certain group. These components were used to calculate precision, recall, accuracy, and F-score. The recall (sensitivity) of this study is the proportion of persons who were accurately diagnosed as having dementia. The success of a diagnostic test for dementia may be gauged by the proportion of people correctly excluded as non-carriers. F1 is a weighted average of recall and precision, while accuracy is the proportion of correctly recognized individuals. The results are summarized and provided to the patient in the form of a report.

	model	best_score	best_params
0	svm	0.946198	{'C': 3, 'kernel': 'linear'}
1	logistic	0.946198	{'penalty': 'l1', 'solver': 'liblinear'}
2	RF	0.943459	{'criterion': 'entropy', 'n_estimators': 300}
3	DT	0.889658	{'criterion': 'gini', 'splitter': 'random'}

Figure 5 : Best params

Figure 5 shows the overall performance of the classifiers. With the help of it we can say that the SVM and Logistic performs best with the accuracy of 94.61% and with best params. The second best algorithm is Random Forest with the accuracy rate of 94.34%.

Dementia is more common in males than in women. There was a greater proportion of people aged 70–80 in the demented group

compared to the non–demented group, and individuals in the demented group had lower levels of schooling than the non–demented. It pinpoints the precise stage of dementia the patient is in. Since the stages are dictated by the responses of the patients, identifying the phases is essential. Clinical staff also benefit from knowing the stage since it helps them to gauge the extent to which the illness has impaired the patient. This study's testing and analysis were conducted using the aforementioned configurations, applications, and libraries.

CONCLUSIONS & FUTURE SCOPE

Dementia is a major health problem, yet preventing it, treating it early, and curing it are all less important than doing the former. It is a major health problem, which is concerned with the curing process. The most important part is to reduce the risk and provide the percentage of the intervention period. It is the process that diagnoses the program from the system early. This literature survey is about detecting samples of dementia diseases with the help of the different parts in the machine learning process and the atrophies. It is the micro process for simulation. Challenge the task and attribute the trick to identify the detection factor. Dementia diseases are the elimination of the redundant factor which is not relevant to the feature of the existing part which is set for the improvements of their accuracy part and detection-related techniques. The ability of this model is to discriminate cases of dementia which means it can be a worthwhile tool to screen patients for trial recruitment and patient management.

By including other factors such as MMSE and Education, we can train our model to distinguish between healthy individuals and those with Alzheimer's disease. It is still unclear whether traits are relevant for early identification of dementia, despite several efforts to do so using various machine learning algorithms and micro-simulation approaches, as reported in the reviewed literature. As a result of this paper, we used Cross Validation, which entails dividing the whole dataset into n-equal-sized halves. The ML model is trained at each iteration using n-1 sub-iterations. Averaging the results from n independent trials allows us to assess the reliability of the procedure. In this case, the ML model was trained and tested 5-times using ten-fold cross-validation. In this paper we concluded that SVM and Logistics performed best with 94.61% accuracy.

Future research will concentrate on the extraction and analysis of unique traits that are more likely to aid in Alzheimer's disease diagnosis, as well as the deletion of redundant and unneeded features from present feature sets to boost the accuracy of detection methodologies.

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