Progression Analysis and Facial Emotion Recognition in Dementia Patients Using Machine Learning

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1 Introduction

Dementia is a term for loss of memory, and other mental abilities severe enough to interfere with daily life [1]. Dementia is not a specific disease; rather, it is an umbrella term that describes a group of symptoms generally related with a decline in memory or other thinking abilities severe enough to hinder a person's ability to perform simple everyday activities [2]. Studies have suggested that MRI features can predict rate of decline of Alzheimer's disease and may help suitable therapy in the future. However, to reach that stage clinicians and researchers will have to make use of machine learning techniques that can accurately predict the progress of a patient from mild cognitive impairment to dementia.

Alzheimer's is the most well-known common type of dementia, though there are numerous kinds that do exist but are in theory, incurable. Brain imaging via magnetic resonance imaging (MRI) is used for the evaluation of patients with suspected AD. MRI findings include both local and generalized shrinkage of brain tissue [3–6].

Although current Alzheimer's treatments cannot stop Alzheimer's from progressing, they can briefly slow down the worsening of dementia symptoms and improve the quality of life for those with Alzheimer's and their caregivers. Today, there is an overall exertion under approach to discover better ways to treat the disease. This paper aims to include collective research and practical implementation which can delay its onset and prevent it from developing [7–10].

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In this paper, a sound machine learning web application is proposed that can help clinicians predict early dementia. Section 1 describes the basic underlying concept of dementia disease and is elaborated with the help of clinical information, Sect. 2 presents progression analysis using machine learning and is performed on the dataset to resolve important conclusions. Exploratory data analysis (EDA) is done on data which is a longitudinal collection of 150 subjects aged 60 to 96. Sect. 3 discusses the concept of facial emotion recognition which is explained and how it can diagnose dementia at an early stage which saves the patient's cognitive abilities to deteriorate further finally in Sect. 4, evaluating the goal of the machine learning web application and how it can help clinicians in determining dementia disease in patients and its scope for battling key challenges in the future of neurological illnesses such as dementia and AD affecting people of all ages. Discussion about further useful functionalities that can be added to the web application which can, in turn, enhance its capability to provide even more promising results in early medical diagnosis.

2 Literature Survey

Alzheimer's is a type of dementia that causes problems with memory, thinking, and behavior. Alzheimer's is certainly not a normal part of aging; a number of ML techniques have been designed to extract features and perform operations on MRI images [11]. To identify affected people, Kloppelet [12] developed a dynamic technique employing weighted MRI-based SVM. Gray et al. [13] employed NB classification for determining a multidimensional classification the AD category. Morra et al. [14] designed a distinction between diversified platform for detecting AD with SVM and AdaBoost hierarchy. An improved DKPCA for AD MRI images was designed [15] by Neffen et. al. New platform design was verified on OASIS samples, and 92.5% accuracy was achieved employing an MSVM. Wang et al. [16] employed equilibrium transformation function to determine features in MRI image, and Ding et al. [17] technique enhanced function recovery. They employed grayscale matrix to differentiate ADNI datasets. Dashan et al. [18] used extract and discount technique of Harvard Medical School's, technique achieved an accuracy from 97 to 98%. Images from the ADNI databases were verified by Hinrich et al. [13]. Yue et al. [19] established a connected removal algorithm on voxels which exposes the relationship among objects. Ahmed et al. [20] designed an easy-to-implement CNN model. The model lowered the cost of computing and vastly increased accuracy of about 91%. Most of the experiments gave results, based on how well features were employed, one potential way to overcome the constraint is by employing deep learning techniques, since these techniques perform automatic selection of features [21].

3 Proposed Methodology

Recognizing dementia in the earlier stages will allow time for carers and those affected by dementia to understand what is happening, plan for future and establish links with support services, thus hopefully preventing crisis situations [4]. To find out the symptoms in which dementia is mainly isolated, we mainly use comprehensive assessment to analyze the symptoms, but the sensitivity of these assessment tools varies depending on age, education, social class, and living situation [5].

Process flow for early identification of dementia comprises of following steps.

i. Medical History Analysis of Subject (Image Processing)

   a. We can add an automated cognitive test which analyzes the facial emotion of subject based on some intuitive questions and closely examine the facial expressions of subject, whether there are any facial expression deficits present.
   b. For example, if the subject is being probed about a particular question, how is the subject reacting with respect to his facial expressions. What facial emotions is the subject conveying?
   c. A ML model is built keeping the aspects of image processing. The model takes facial portraits of the subjects (young, middle-aged, old men, or women) as input and analyzes those images by predicting the emotion displayed by subject. The model can classify the images into seven emotions—anger, disgust, fear, happy, sad, surprise.

ii. Computer-Based Test

   a. In this step, we include a system that can perform computer-based tests, based on medical technique of FCSRT. We conduct something like “Active recall” for the patients, i.e., Free and Cued Selective Reminding Test (FCSRT)
   b. The subjects(patients) search for items (e.g., apple—could be any object) in response to cues (fruits) and then further used to recall more similar items.
   c. Performance on the FCRST distinguishes dementia from normal aging with accuracy.
   d. We can build a system that requires the subject to draw/imitate an item from memory given the cues. After that, the subject’s imitation and the actual item can be compared.

iii. Prescribed Tests/Screening Tests

   a. A standard medical workup for dementia often includes structural imaging with magnetic resonance imaging (MRI) or computed tomography (CT).
   b. A system can be built using ML that takes the subjects’ MRI and after analyzing it, labels it as normal or abnormal.

c. It can be an interface where the subjects would be required to upload their MRI scans, and the model would look for abnormalities by comparing it to a normal brain imaging subject.

4 Implementation and Result: Progression Analysis Using Machine Learning

Progression analysis employs machine learning to comprehend the parameters that work is being implemented. Analysis main aim is to find hidden details that affect the slope of deterioration of dementia. Starting with the data, which is fundamental in implementing any machine learning algorithm, further Exploratory Data Analysis (EDA) is done alongside with some data preprocessing to ensure the machine learning model that will perform well. Further, discussion is done regarding the classification algorithm used for the model that is random forest classifier along with the result obtained [6] (Table 1).

Dataset consists of a longitudinal collection of 150 subjects aged 60 to 96. Each subject was scanned on two or more visits, separated by at least one year for a total of 373 imaging sessions. For each subject, three or individual T1-weighted MRI scans obtained in single scan sessions are included. The subjects are all right-handed and include both men and women. Seventy-two of the subjects were characterized as non-demented throughout the study. Sixty-four of the included subjects were characterized as demented at the time of their initial visits and remained so for subsequent scans, including 51 individuals with mild to moderate Alzheimer's disease. Another 14 subjects were sorted as non-demented at the time of their initial visit and were subsequently characterized as demented at a later visit.

Table 1 Column descriptors

Column name	Description
EDUC	Years of education
SES	Socioeconomic status
MMSE	Mini-mental state examination
CDR	Clinical dementia rating
eTIV	Estimated total intracranial volume
nWBV	Normalize whole brain volume
ASF	Atlas scaling factor

Table 2 Cognitive impairment scale

Method	Score	interpretation
Single cutoff	< 24	Abnormal
Range	< 21	Increased odds of dementia
	< 25	Decreased odds of dementia
Education	21	Abnormal for 8th-grade education
	< 23	Abnormal for high school education
	< 24	Abnormal for college education
Severity	24–30	No cognitive impairment
	18–30	Mild cognitive impairment
	0–17	Severe cognitive impairment

4.1 Mini-Mental State Examination (MMSE)

The Mini-Mental State Examination (MMSE) or Folstein test is a 30-point questionnaire that is used extensively in clinical and research settings to measure cognitive impairment [7]. Any score greater than or equal to 24 points (out of 30) indicates a normal cognition. Below this, scores can indicate severe (≤9 points), moderate (10–18 points), or mild (19–23 points) cognitive impairment (Table 2).

4.2 Clinical Dementia Rating (CDR)

The CDR is a 5-point scale used to characterize six domains of cognitive and practical performance appropriate to Alzheimer. The CDR table provides descriptive secures that help the clinician in making fitting evaluations dependent on questionnaire data and clinical judgment. This score is useful for characterizing and tracking a patient's level of impairment/dementia (Table 3).

Table 3 Clinical dementia rating (CDR)

Score	Description
0	Normal
0.5	Very mild dementia
1	Mild dementia
2	Moderate dementia
3	Severe dementia

4.3 Estimated Total Intracranial Volume (eTIV)

Total intracranial volume (TIV/ICV) is a significant covariate for volumetric investigation of the brain and cerebrum regions, particularly in the investigation of neurodegenerative diseases. Unlike brain decay in the patients with AD, TIV did not change over time. The only huge predictor of TIV was gender. Men showed an approximately ~12% larger eTIV than women [8].

4.4 Atlas Scaling Factor (ASF)

ASF is a normalization technique to measure the standardized total intracranial volume for comparison, classification and predication in benign and infected cases for all age groups [9].

4.5 Exploratory Data Analysis (EDA)

Dataset is further investigated for the relationship between each feature of MRI tests and dementia of the patient. It might help us to understand the nature of the data and to select the appropriate analysis strategy method for the model later (Table 4; Fig. 1).

This chart indicates that there is a higher concentration of 70–80 years old in the demented patient group than those in the non-demented patients. Patients who suffered from that kind of disease have lower survival rate so that there are a few of 90 years old (Fig. 2).

This chart shows that non-demented group has much higher MMSE scores than demented group (Figs. 3, 4, and 5).

From the above charts, we can conclude that non-demented group has a higher brain volume ratio than demented group based on the assumption that neurological diseases affect the brain to be shrinking its tissue.

Table 4 Minimum, maximum, and average values of each feature

	Min	Max	Mean
Educ	6	23	14.6
SES	1	5	2.34
MMSE	17	30	27.2
CDR	0	1	0.29
eTIV	1123	1989	1490
nWBV	0.66	0.837	0.73
ASF	0.883	1.563	1.2

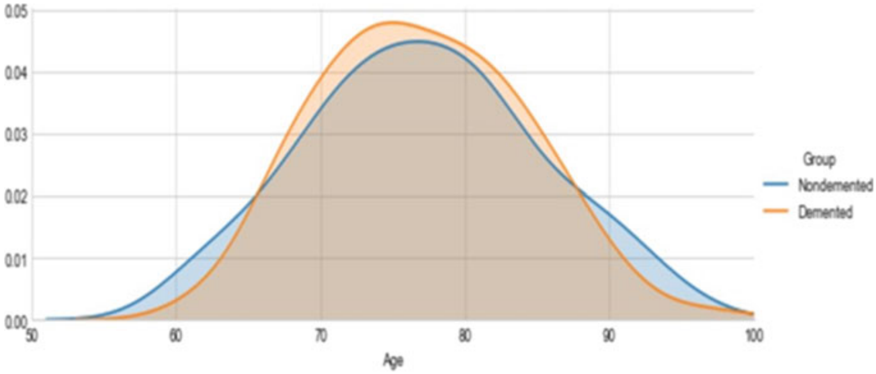

Fig. 1 Age versus non-demented and demented

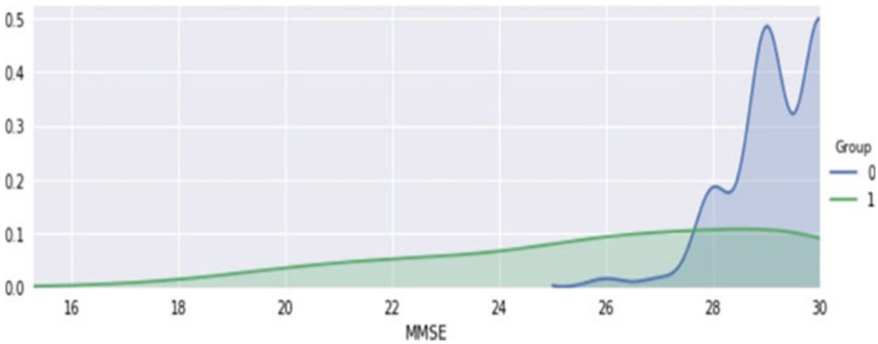

Fig. 2 Mini-mental state examination

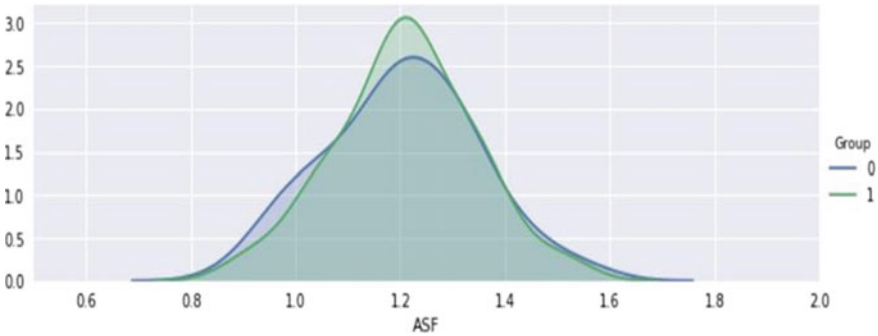

Fig. 3 ASF: Atlas scaling factor

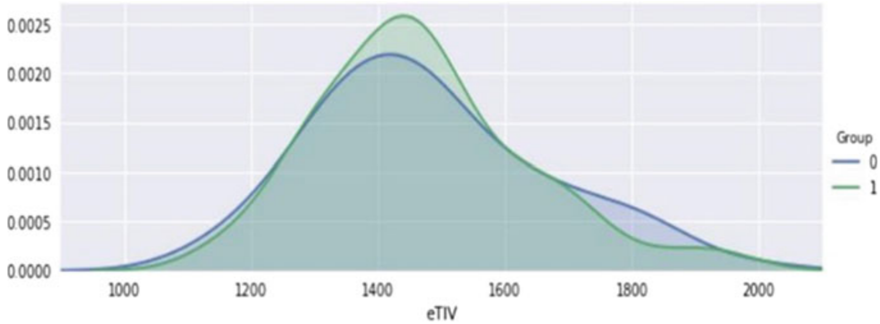

Fig. 4 eTIV: Estimated total intracranial volume

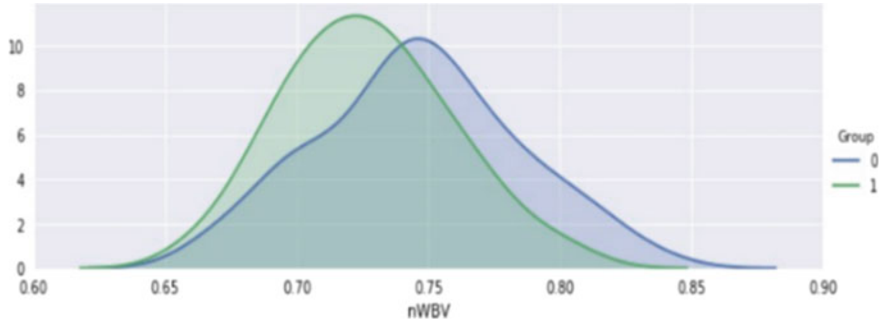

Fig. 5 nWBW: Normalized whole brain volume

4.6 Building the Machine Learning Model

The area under the receiver operating characteristic curve (AUC) is considered as the main performance measure here. It is assumed that in case of medical diagnostics for non-life-threatening terminal diseases like most neurodegenerative diseases, it is important to have a high true positive rate so that all patients with Alzheimer's are identified as early as possible. But we also want to make sure that the false positive rate is as low as possible since we do not want to misdiagnose a healthy adult as demented and begin medical therapy. Hence, AUC seemed like an ideal choice for a performance measure. Random forest, like its name implies, consists of a large number of individual decision trees that operate as an ensemble. Each individual tree in the random forest spits out a class prediction and the class with the most votes becomes our model's prediction [10]. Result obtained is depicted in figure, and accuracy for the model achieved from the proposed technique is 0.8393 or 84% (Figs. 6 and 7).

Paper also incorporates facial emotion recognition in dementia patients. As discussed, delayed diagnosis of dementia is one of the main challenges that keeps patients from having proper healthcare aid at the correct time. Most dementia patients

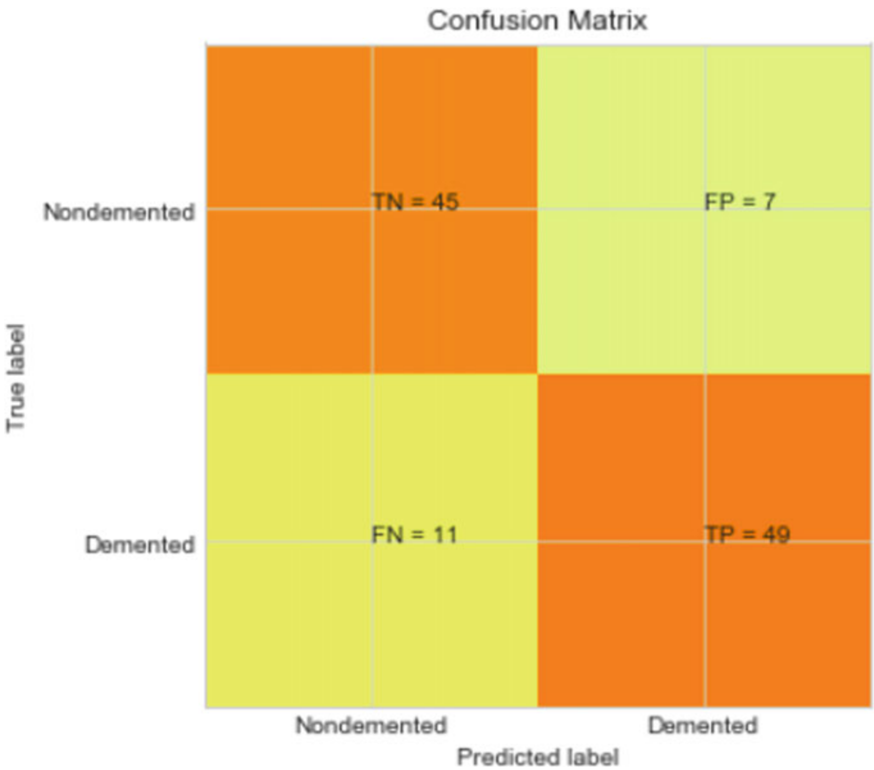

Fig. 6 Classification report and confusion matrix for the model

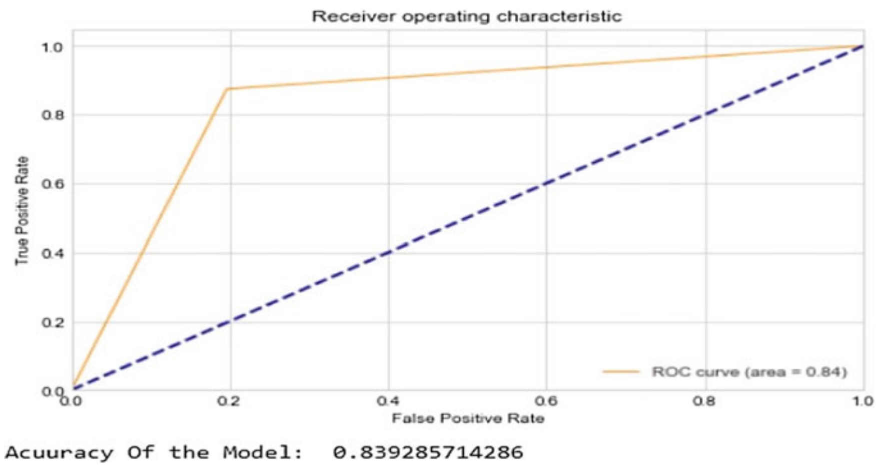

Fig. 7 Receiver operating characteristics for the proposed model

are diagnosed with dementia and its related variants much later than required which leads them to lead a very difficult lifestyle that pertains to depleting cognitive abilities which in turn leads to complications that put these underdiagnosed patients in a lot of danger.

In this part of the webapp, an automated cognitive test is added which analyzes the facial emotion of subject based on some intuitive questions and closely examine the facial expressions of subject, whether there are any facial expression deficits present [11]. For example, if the subject is being probed about a particular question, how is the subject reacting with respect to his facial expressions. What facial emotions is the subject conveying?

A ML model is built keeping the aspects of image processing. The model takes facial portraits of the subjects (young, middle-aged, old men, or women) as input and analyzes those images by predicting the emotion displayed by subject. The model can classify the images into seven emotions—anger, disgust, fear, happy, sad, surprise, and neutral. The dataset used was mainly imaged (in jpeg format) from FACES (a database of facial expressions in young, middle-aged, and older women and men).

Work used two main libraries OpenCV and facial emotion recognition 0.3.4. OpenCV is the huge open-source library for the computer vision, machine learning, and image processing and now it plays a major role in real-time operation which is very important in today's systems. Facial emotion recognition 0.3.4 is a pre-weighted open-source library released in October 2020 (Fig. 8).

Fig. 8 Images from sample dataset

5 Conclusion

Work proposed employs simple but powerful machine learning techniques to create valuable advancements in the medical domain. Mental illnesses such as dementia and AD are often overlooked, when they can be diagnosed using such unique functionalities which are flexible enough to be used by one regarding their programming background. Clinicians can be highly benefitted from such creative intelligent applications which can assist them to identify dementia and similar neurological diseases that can be easily identified using MRI scans and collaborative cognitive tests. Developing the current webapp into an efficient robust machine learning system that can be efficiently used in various other functionalities that can help to determine dementia at an early stage. Adding more complex functionalities such as a replication interface of the medical technique called FCSRT. We can conduct something like "Active recall" for the patients, i.e., Free and Cued Selective Reminding Test (FCSRT). In this technique, the subjects(patients) search for items (e.g., apple—could be any object) in response to cues (fruits) and then further used to recall more similar items. Performance on the FCRST distinguishes dementia from normal aging with accuracy. According to World Health Organization (WHO), more than 50 million people have dementia worldwide and approximately 10 million new cases are reported every year. Thus, there is need to spread awareness which will help the community to know about this disease. Model designed achieves an accuracy of 84% which is at par with existing models.

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