Retraction

Retraction: An Effective Dementia Diagnosis System using Machine Learning Techniques (J. Phys.: Conf. Ser. 1916 012173)

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This article (and all articles in the proceedings volume relating to the same conference) has been retracted by IOP Publishing following an extensive investigation in line with the COPE guidelines. This investigation has uncovered evidence of systematic manipulation of the publication process and considerable citation manipulation.

IOP Publishing respectfully requests that readers consider all work within this volume potentially unreliable, as the volume has not been through a credible peer review process.

IOP Publishing regrets that our usual quality checks did not identify these issues before publication, and have since put additional measures in place to try to prevent these issues from reoccurring. IOP Publishing wishes to credit anonymous whistleblowers and the Problematic Paper Screener [1] for bringing some of the above issues to our attention, prompting us to investigate further.

[1] Cabanac G, Labbé C and Magazinov A 2021 arXiv:2107.06751v1

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An Effective Dementia Diagnosis System using Machine Learning Techniques

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Abstract. Dementia being a major cause of creating dependency among aged people also has an inevitable impact on people suffering from it and the families around them. Since the symptoms are gradual and may overlap, diagnosing dementia and identifying its type is risky. The main purpose is to develop a machine learning-based method in diagnosing dementia using the dataset obtained from OASIS. Algorithms such as Support Vector Machine, AdaBoost, K-Nearest Neighbors, Random forest, Linear Discriminant Analysis, XgBoost algorithms are used to find accuracy, recall, and confusion matrix. Implementation of the following algorithms provides accuracy in the range of 83 to 90 percent. SVM provides 87%, KNN gives out accuracy of 84%, LDA gives an accuracy of 83%, Random forest gives an accuracy of 88%, AdaBoost gives 81% and XgBoost gives 90%. XGBoost shows more accuracy than other algorithms.

1. Introduction
Neurocognitive disorder (NCD) primarily affects cognitive skills such as learning, memory, perception, and problem solving. There are various types of cognitive disorders stated by Diagnostic and Statistical Manual (DSM) of mental disorders. Dementia is a collective term to denote the group of cognitive decline symptoms. The World Health Organization (WHO) describes dementia as deterioration in memory, thinking and behaviour which impacts everyday activities. Nearly 50 million people are affected by dementia. Around 10 million new cases each year. This states that at least one individual case is reported every 3.2 seconds. Dementia mostly affects aged people, but this does not mean young people are not affected by it. According to a report in 2020, it is known that 5.3 million individuals above the age of 60 have developed dementia in India which is one in every 27 people. Various types of dementia include Alzheimer’s, Lewy Body Disease, Frontotemporal dementia, Vascular dementia and more. Out of those Alzheimer’s disease alone contributes 60 to 80 percent of dementia cases making it the most common type. Aging is the greatest known factor for causing Alzheimer’s however Alzheimer’s is not an old age disease. Reduced blood flow due to narrowing and blockage of blood vessels in the brain causes vascular dementia. Mixed dementia is a condition where one has both vascular and Alzheimer’s together. In mixed dementia, it’s hard to find the amount of contribution of each type in the affected person. Lewy body disease is caused by alpha-synuclein protein clumps which developed inside brain cells. Frontotemporal dementia is seen in people of the age group 45 to 65. In frontotemporal dementia, nerve cells in both frontal and temporal lobes are damaged and shrunk due to the protein clumps. There are some rare causes for dementia which contributes less than 5% of
dementia cases which are Huntington's disease, cortico-basal degeneration, progressive supranuclear palsy, normal pressure hydrocephalus.

Symptoms of dementia include cognitive, behavioral, psychological changes in activity. Disorientation, confusion in mental state, inability to recognize, changes in personality, restlessness, wandering or forgetting routes, hallucination, mental depression, memory loss, jumbled speech, unsteady walking are some symptoms of dementia. Diagnosis of dementia is challenging. A pattern recognition of loss of skills and function in a patient must be studied by the doctor to diagnose the cause of dementia. Biomarkers are made available these days to diagnose dementia more accurately. Cognitive tests, neuropsychological tests and evaluation, laboratory tests, psychiatric evaluation, brain scans such as CT, MRI, PET are used to identify and diagnose the symptoms of dementia. Mostly dementia is not curable however the condition of the patient can be improved. Medications, therapies, lifestyle and home remedies are used to manage and improve dementia.

In this paper, machine learning techniques are applied on OASIS dataset that has the data of demented, non-demented individuals. Machine learning has been implemented in various fields for the betterment of analyses and results, the health sector is the major area where the contribution of machine learning is found to be most useful. The main aim is to build a machine learning model that can diagnose dementia with better accuracy. In this paper, SVM, KNN, LDA, Random Forest, AdaBoost and XGBoost will be implemented.

2. Related Works
[1] proposed a machine learning model for identifying Parkinson. Their goal is to identify complex diseases like Alzheimer's, frontotemporal dementia, and Parkinson's. Since the symptoms of these diseases are a little difficult to diagnose, further research is needed to attain the best outcome. They used a UCI dataset. To measure the precision, recall, and confusion matrix, they used algorithms like support vector machines, K-nearest neighbours, and linear discriminant analysis. Five parameters of the dataset are important for the diagnosis of dementia disorder, and implementation was performed with two separate models. All of the parameters are included in the first version, although only the five key parameters are included in the second version. The training set is 70% and the test set is 30% of the time in both situations. SVM shows higher accuracy in both implementation models.

[2] proposed a model to detect dementia, and suggested a machine learning model its goal is to create a machine learning technique that is remarkably precise and it functions to diagnose and predict neurological disorders as computing power has increased dramatically. This study used a variety of machine learning techniques, such as random forests, support vector machines, artificial neural networks, Naive Bayes, logistic regression, decision trees, and K-nearest neighbour, to find which technique shows the best accuracy. On datasets from open access repositories, Alzheimer's disease neuroimaging initiative, and dementia bank datasets, support vector machine and random forest outperform all other algorithms.

[3] proposed a deep learning model Predicting Dementia and Mild Cognitive Impairment. Their aim is to examine ADNI data and test its feasibility for developing classification models in order to distinguish the categories Cognitively Normal, Moderate Cognitive Disability, and Dementia, based on the tuning of three Deep Learning models: two Multi-Layer Perceptron models and a Convolutionary Bidirectional Long Short-Term Memory (ConvBLSTM) model. Although the ConvBLSTM model was less accurate than the MLP models, it was investigated because of similarities with them and the possibility of future extensions of this work that would take advantage of time-related data. While the ConvBLSTM model's output was hampered by a lack of data on the visit code, there were areas where it could be improved, especially in terms of pre-processing.

[4] applied the C4.5 guidelines, C4.5, Naïve Bayes, IB1, to test data collected from two basic cognitive and functional skills assessments, FAQ and BOMC, to enhance dementia screening. Data is gathered at Irvine ADRC, from the University of California. Compared with the classifiers, such as RBF Neural Networks, MLP Neural Networks, SVM, Random Forests, Chaid, Cart and Search classification trees were (Quadratic Discriminant Analysis, Logistic Regression and LDA) [5]. For the prediction of
dementia, the ten different neuropsychological tests were used, and it is demonstrated that Random Forest and LDA display high precision, specificity, discriminant capacity and sensitivity.

[6] proposed a comparative analysis of various machine learning algorithms for detecting dementia. They have developed a comparative analysis model with J48, Naïve Bayes, Random Forest and Multilayer Perceptron. They have used CFSSubsetEva for the attribute reduction. J48 has been found to be the most effective of all the algorithms for detecting dementia.

[7] proposed a machine learning model that uses algorithms such as Support Vector Machine, Ada boost, LogitBoost, MLP, Naïve bayes, and Random forest to maximise the amount of neuropsychological measures used to diagnose dementia patients and to build and verify an effective classification model based on the diagnostic details of enrolled subjects. It has been found that SVM and MLP is performing best among six classification models.

[8] proposes an automated image processing-based approach for the identification of AD from MRI of the brain. Patients diseases are identified using three separate classification models (SVM, MLP, and J48). An ensemble of classifiers is used in addition to the above three classifications to solve the error induced by an individual base classifier. Their scheme is evaluated using a ten-fold cross validation approach. Specific features and combinations of features are often fed to individual classifiers and ensemble-based classifiers to determine the success of the proposed solution.

3. Methodology
Explanation and prediction are two important goals of machine learning algorithms. Using the variables in the database, the assumptions can be predicted. Predictions can be developed by predicting peculiar or future values of unknown or possible interest values using current variables [9].

In order to get the best result from the machine learning algorithm, flow has to be followed. First of all, for implementing the machine learning algorithms dataset is required. After collection of data, the collected dataset should be processed to make that dataset suitable for the model. Once all the processing is done, we will split the dataset into two categories as testing and training dataset and feeding dataset to the model. At last, the model will be able to diagnose dementia from the given dataset.

This is the flow used for machine learning model implementation to get the best result from the model Figure 1.

![Flow diagram of the machine learning model](image.png)

3.1. Dataset description

Name: MRI and Alzheimer’s [10]
Source: Kaggle
Description: Longitudinal MRI Data in Nondemented and Demented Older Adults, this dataset has 373 records which is collected from the single scan session of the participants. Attributes used are shown in table 1.

Table 1. Attributes in selected dataset

| OASIS Longitudinal | Description                  |
|--------------------|------------------------------|
| Subject ID         | Subject Identification       |
| MRI ID             | MRI Exam Identification      |
| Group              | Class                        |
| Visit              | Visit order                  |
| M/F                | Gender                       |
| Hand               | Dominant Hand                |
| Age                | Age in years                 |
| Educ               | Education level              |
| SES                | socioeconomic status         |
| MMSE               | Mini Mental State Examination|
| CDR                | Clinical Dementia Rating     |
| MR Delay           | MR Delay time (Contrast)     |

3.2. Data pre-processing

For producing the best outcome, data pre-processing is the method of getting data ready. Data pre-processing helps to make the dataset suitable for our machine learning model [11]. Data pre-processing involves different steps, such as

- Obtaining the dataset
- Importing libraries and datasets
- Finding the Missing Data
- Categorical Data Encoding
- Splitting of training and test dataset
- Feature scaling

Data Pre-processing, a very significant phase where the results are interfered with by noisy data and can lead to misleading consequences [12-15]. Since most of the fields in the data set are categorical variables, the variables must be encoded before the model is applied to them. Data was cleaned by null records filled in followed by categorical variables encoded. For all fields with categorical variables, dummy variables were generated to turn them into binomial variables (i.e 0 or 1) in figure 2.
The processed data contains 373 participants with 15 input attributes, and one output attribute. The train and test data used for evaluating the performance of the model is split into seventy-thirty ratios.

### 4. Machine Learning Algorithms for Dementia Diagnosis

#### 4.1. Support Vector Machine (SVM)

Support vector machine algorithm work by finding a hyperplane that separates the data points and classifies them into dimensional space depending on the number of features. Several potential hyperplanes can be used in order to separate and layout differences among the two groups of data points [16-20]. A highest margin planes whose distance between the data points between two classes is maximum is chosen to analyse. Increasing the gap from the margin lends support for classifying data points in future.

#### 4.2. K-Nearest Neighbors (KNN)

The K-Nearest Neighbors algorithm, considered as one of the most basic algorithms, works by classifying data into categories. Though the algorithm is widely used in classification it is also used in regression-based problems. Training a dataset in KNN is fast when compared to prediction. KNN uses the Euclidean distance metric to calculate the distance between new data point from each and every data point present and finds the next nearest neighbors. The main goal of KNN is reduction of variance. When the value of K is equal to the number of data points present then the model is said to have low variance and when K is equal to 1 then the model has high variance. KNN involves initializing and defining K, distance calculation, sorting, finding nearest neighbors, getting its category and finding out its majority [21].

#### 4.3. Linear Discriminant Analysis (LDA)

LDA is used for dimensionality reduction which is used to pre-process data in pattern analysis. When data is huge it consumes more space while processing so the dimensions of the data is reduced. Linear Discriminant Analysis finds the area that maximizes the separation between multiple classes. Firstly, LDA calculates the mean vector, scatter for the whole group and for representatives of the same class. LDA helps in finding boundaries around clusters of classes. It projects the data points in a scalar form so that the clusters are as separated as possible, with each cluster having a relative (close) distance to a centroid. The main task of LDA is to maximize the distance between the discriminating boundary or the
discriminating line to the data points on either side of the line and minimize the distances between the points themselves [22].

4.4 Random Forest (RF)
Random Forest is one of the bagging techniques present. Many individual decision trees form the random forest algorithm. Like the divide and conquer method, random forest works by calculating the weighted average of nodes reached so far [23]. This algorithm can work well with unbalanced or missing data. It can handle large datasets that have a high number of dimensions. It gives a good accuracy rate with small datasets, but it is ineffective in real time predictions. In our model the count of estimators (n_estimators) which represents the number of decision trees used within the random forest is chosen as 200 and the scale of splitting data into decision trees is set to auto.

4.5 AdaBoost
Adaptive boosting is one of the ensemble boosting classifiers which was proposed by Yoav Freund and Robert Schapire. AdaBoost is an iterative ensemble system. It incorporates several classifiers to improve classifier accuracy. The AdaBoost classifier generates an efficient classifier by mixing several poorly performing classifiers, resulting in a strong classifier with high accuracy. Adaboost's core concept is to set the weights of classifiers and train the sample data in each iteration to ensure that unusual observations are correctly predicted. Any machine learning algorithm can be used as a reference classifier if it accepts weights from the training set. Two conditions should be met by Adaboost
1. Different weighted training examples should be interactively trained by the classifier.
2. In each iteration, by minimizing training errors, it aims to provide an excellent match for these instances.

4.6 Extreme Gradient Boosting (XG Boost)
XGBoost stands for eXtreme Gradient Boosting. XGBoost is an ensemble Machine Learning algorithm that uses a gradient boosting structure and is built on a decision tree. When it comes to small-to-medium structured/tabular data, however, decision tree-based algorithms are currently considered best in class. In prediction problems affecting unstructured data (image, text, etc), artificial neural networks appear to outperform all other algorithms.

5. Results and Discussion
The machine learning algorithms such as SVM, KNN, LDA, RF, ADA BOOST and XGBOOST are selected to implement oasis cross sectional and oasis longitudinal data. On each algorithm accuracy, precision, recall and F-score are calculated.

5.1 Evaluation parameters
The models are evaluated based on the following parameters equation 1-3

\[
\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}
\]

\[
\text{Precision} = \frac{TP}{TP + FP} \tag{1}
\]

\[
\text{Recall} = \frac{TP}{TP + FN} \tag{2}
\]

\[
F1\ Score = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{3}
\]
The Area Under the Curve (AUC) is a performance metric for classification problems at different threshold settings. The degree or measure of separability is represented by the AUC, which is a probability curve. It clarifies the model's ability to distinguish between classes. The AUC is determined by how well the model predicts 0s as 0s and 1s as 1. By comparison, the better the model is to differentiate between patients with the disease and no disease, the higher the AUC.

5.2 Experimental Results

Precision, Recall, F-Score and Accuracy for implementation with all features in percentage are shown in table 2 and table 3.

Table 2. Comparison of performance metrics of implementation with all features - Demented

| Measures   | SVM | KNN | LDA | RF  | ADA_BOOST | XGBOOST |
|------------|-----|-----|-----|-----|-----------|---------|
| Accuracy   | 75% | 67% | 72% | 84% | 79%       | 83%     |
| Precision  | 79% | 79% | 82% | 85% | 81%       | 86%     |
| Recall     | 73% | 55% | 62% | 87% | 80%       | 82%     |
| F1 Score   | 76% | 65% | 70% | 86% | 71%       | 84%     |

Table 3. Comparison of performance metrics of implementation with all features - Non demented

| Measures   | SVM | KNN | LDA | RF  | ADA_BOOST | XGBOOST |
|------------|-----|-----|-----|-----|-----------|---------|
| Accuracy   | 75% | 67% | 72% | 84% | 79%       | 83%     |
| Precision  | 71% | 61% | 66% | 84% | 77%       | 80%     |
| Recall     | 77% | 83% | 85% | 83% | 79%       | 85%     |
| F1 Score   | 74% | 70% | 74% | 83% | 78%       | 82%     |

Table 4. Comparison of performance metrics of implementation with 8 features - Demented

| Measures   | SVM | KNN | LDA | RF  | ADA_BOOST | XGBOOST |
|------------|-----|-----|-----|-----|-----------|---------|
| Accuracy   | 87% | 84% | 83% | 88% | 81%       | 90%     |
| Precision  | 96% | 72% | 97% | 91% | 79%       | 92%     |
| Recall     | 79% | 55% | 70% | 86% | 82%       | 88%     |
| F1 Score   | 86% | 63% | 81% | 88% | 81%       | 90%     |
Table 5. Comparison of performance metrics of implementation with 8 features - Non-Demented

| Measures      | SVM  | KNN  | LDA  | RF   | ADABOOST | XGBOOST |
|---------------|------|------|------|------|----------|---------|
| Accuracy      | 87%  | 84%  | 83%  | 88%  | 81%      | 90%     |
| Precision     | 82%  | 64%  | 76%  | 86%  | 81%      | 88%     |
| Recall        | 96%  | 79%  | 98%  | 91%  | 79%      | 93%     |
| F1 Score      | 89%  | 70%  | 86%  | 89%  | 80%      | 90%     |

Confusion matrix and ROC for algorithms such as SVM, KNN, LDA, RF, ADA BOOST and XGBOOST has been shown in figure 3 - 14.

Figure 3. Confusion matrix for SVM

Figure 4. ROC for SVM

Figure 5. Confusion matrix for KNN

Figure 6. ROC for KNN

Figure 7. Confusion matrix for LDA

Figure 8. ROC for LDA
Figure 9. Confusion matrix for RF

Figure 10. ROC for RF

Figure 11. Confusion matrix for ADABOOST

Figure 12. ROC for ADABOOST

Figure 13. Confusion matrix for XGBOOST

Figure 14. ROC for XGBOOST

Figure 15. Accuracy rate for all algorithms with all features

Figure 16. Accuracy rate for all algorithms with 8 features
From figure 15 and 16 comparing implementation with all features and with selected eight features, the machine learning model shows some difference. So, based on the results we obtained in our model, the XGBoost of selected eight features had the best accuracy in detecting dementia.

6. Conclusion and Future Work

In current research, the effort is to experiment with Alzheimer's data with machine learning algorithms to diagnose dementia. In total, 15 data attributes are taken into account. The work began with 373 Alzheimer's data and with the deployment of algorithms such as SVM, LDA, KNN, RF, AdaBoost and XGBoost, which is evidence that machine learning algorithms are now used to identify brain diseases. This form of diagnosis aims to save time for neurologists and patients to get the correct diagnosis at the right time.

Nearly 90% accuracy of Alzheimer's patient data is demonstrated by the outcome of implementation. The implementation involves 373 Alzheimer's disease details. Similarly, the diagnosis of brain disorders such as frontotemporal dementia can be extended. In the first phase, these diseases don't really display any symptoms, but during MRI, neurologists can predict it in certain intervals after 2nd and 3rd MRI scans. Thus, using machine learning methods, such diseases can be diagnosed with better accuracy.

In the future, brain diseases such as cerebral microbleeds, holes, cortical cerebral micro facts, quantified volumes of subcortical structure, grey matter densities etc., must be considered in order to diagnose other dementia.

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