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Research Article

Early Detection of Alzheimer's Disease Using Cognitive Features A Voting-Based Ensemble Machine Learning Approach

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ABSTRACT

Early detection is key to effective care of Alzheimer's disease. Quicker treatment and better outcomes are possible with early disease detection. This work uses cognitive characteristics and ensemble machine learning to diagnose Alzheimer's. Ensembles improve forecast accuracy by combining machine learning algorithms. Cognitive tests from Alzheimer's patients and healthy controls are cleaned up into a dataset. This data underpins machine learning. Features are selected to highlight the most relevant cognitive traits for Alzheimer's disease identification. This stage helps identify the most symptomatic cognitive features of the illness. Neighborhood Component Analysis and Correlation-based Filtration are unique feature selection methods in this work. Selecting essential cognitive traits from the dataset enhances AD diagnosis. Alzheimer's disease detection is greatly improved by the proposed method. This improvement is essential for early AD detection and treatment. This study detects early Alzheimer's disease 100% of the time using CNN, CNN with Long Short-Term Memory (LSTM), and an effective Stacking Classifier.

Keywords: *Adaptive voting, Alzheimer's disease (AD), cognitive features, machine learning (ML), Neighborhood Component Analysis and Correlationbased Filtration (NCA-F)*

INTRODUCTION

Signs epithetical Alzheimer's disease (AD) initially appear slowly, but over time they get worse. It affects a wide range epithetical brain processes. Memory loss, including forgotten names, places, things or recent interviews, is the most important symptom epithetical Alzheimer's disease. Other symptoms & worsening epithetical the memory problem abide characterized by the advanced Alzheimer's disease. These include confusion, disorientation & even lost in a familiar environment. Most AD cases occur in the 65 & older ones. As people age is more likely towards develop Alzheimer's disease & other forms epithetical dementia. For example, Alzheimer's disease affects 1 epithetical 14 people aged 65 & 1 epithetical 6 people aged 80 & over [1]. Consequently, early intervention may endure possible among specific & early signs epithetical AD. Because determining the specific subtype epithetical dementia is so difficult, AD prediction is fraught among difficulty [2]. Approximately two-thirds epithetical all dementia diagnoses abide attributable towards AD, according towards the research [3]. The effects epithetical Alzheimer's disease (AD) on people's lives, their families, & healthcare systems have prompted some researchers towards employ mathematical modeling towards foretell the disease's trajectory. Life expectancy, mortality rates, & cardiovascular diseases abide some epithetical the aspects certain these studies take into account. Sadly, the results epithetical these investigations point towards an ever-increasing prevalence epithetical AD [4]. For instance, estimates put the number epithetical Australians afflicted among dementia at between 460,000 & 459,00 in the year 2030 [5]. Similarly, even after adjusting for the anticipated improvement in life expectancy, the number epithetical individuals diagnosed among dementia in England & Wales will climb by 57% from 2016 towards 2040, reaching over 1.2 million [4].

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From 6.08 million in 2017 towards the estimated 15 million in 2060, according towards projections, the number epithetical Americans living among Alzheimer's disease or serious cognitive damage would increase dramatically [6]. On the contrary, advanced health care systems in countries such as the United Kingdom are, according towards recent evidence [7], [8] associated among a decrease in etc. For example, the prevalence epithetical Ad -specific for age has decreased over the past two decades when comparing data from three English regions concerning those who aged 65 & over [7]. In addition, in 2018 there were 69,478 deaths due towards dementia & AD in England & Wales, resulting in the age level epithetical mortality (AMSR) 123.8 per 100,000 people. In 2019, this rate was much lower towards 115.1 per 100,000 people. [7].

Dementia can endure prevented or slowed down in its progression, according towards recent research [8]. This is possible through early detection & intervention strategies. In order towards forecast AD, machine learning (ML) approaches employ neuropsychological assessments [9]. Dementia prediction also makes use epithetical other new ML techniques as convolutional neural networks [12], Adaboost, deep belief network [11], support vector machines (sVM) & stacking AUTOCODER [10]. ML methods can usually predict the onset epithetical Alzheimer's disease in new patients by first learning complex neuropsychological patterns epithetical patients among AD in training samples. It is common for these ML algorithms towards train in the dark. All patients in a dataset abide utilized for training, among the exception epithetical the ones used for prediction.

Contrarily, ML methods for AD prediction abide similar towards real-world clinical settings. The findings epithetical neuropsychological tests can endure used towards anticipate the main pathology epithetical a new patient in clinical scenarios. Machine learning models use these same tests for dementia prediction [13]. So, this study suggests a machine learning ensemble model certain uses adaptive voting towards forecast the onset epithetical AD. Using the filtered cognitive characteristics provided by the new Analysis epithetical neighborhood components & approach based on correlation (NCA-F), several ML classifiers were trained [45]. All the advantages epithetical classifiers for different types epithetical disease detection abide integrated into the proposed strategy. When employing a classifier epithetical the file learning, the model's performance was noticeably improved. In order towards improve the generalization & resistance towards a single estimate, the learning epithetical a set epithetical predictions, instead epithetical discrete labels, all basic classifiers combines. Depending on the method epithetical selecting elements epithetical the file, it significantly increases the accuracy epithetical advertising prediction. Better advertising forecasts in the early phase have also been achieved by incorporating the proposed new strategy certain relies only on cognitive features into ML models.

LITERATURE SURVEY

Dementia most often affects the elderly due towards Alzheimer's disease (AD) [11]. It is assumed certain the first deposits epithetical AD pathology begin about ten towards fifteen years before the start epithetical clinical symptoms, according towards cliniccopatological investigation, indicating the existence epithetical a lengthy foreclinical phase epithetical the disease. Improvement in two or more cognitive domains, usually affecting powerful skills & episodic memory, towards the extent certain it disrupts social or professional functioning among a characteristic clinical profile epithetical Alzheimer's disease. [1] Most patients can endure correctly identified as ad using current diagnostic criteria. Interest in identifying individuals in early symptomatic & presymptomatic stages epithetical the disease is increasing as treatment epithetical modifying disease is developing. This is because these individuals can have the best chance towards respond towards these drugs. towards identify people in the early stages epithetical mild cognitive damage, it is recommended towards use methodologies based on informants towards determine a cognitive & functional decline from the previously achieved performance level.

We have assessed the possible effects epithetical primary & secondary prevention in the US & assumed prevalence epithetical preclinical & clinical Alzheimer disease (AD) [11]. We projected the American population & included biomarkers for preclinical advertising in the multistate model. In 2017, as a result epithetical Ad 6.08 million Americans, as a result epithetical ad. By 2060, this number is expected towards increase towards 15.0 million. Although many epithetical them may never have towards develop a fully blown Alzheimer's disease, 46.7 million Americans lived among a preclinical AD in 2017 (amyloidosis, neurodegeneration or both). [6] The future load on the disease is influenced by the strategies epithetical primary & secondary prevention differently. Our findings emphasize the need for primary & secondary preventive strategies for people without foreclinical AD & for those who

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already have existing brain pathology AD, who abide likely towards develop clinical diseases as a result epithetical high prevalence epithetical preclinical, during their lives.

Several major epidemiological studies have shown certain the incidence epithetical dementia is decreasing in countries among high income. [8] We tried towards characterize the decreasing occurrence epithetical dementia between the subsequent native cohorts in the population sample epithetical the United States & explore the roles certain sex & education play in this trend. Survey Independent Elders Monongahela Valley (1987–2001) & the Monongahela-Youghioghenes team epithetical healthy aging (2006-hongoing) were two community samples certain had comparable study goals & neighboring sampling regions. Their data was combined. From 1902 towards 1941 we were able towards divide the population into four different births. [8] From 3 010 participants (61 percent epithetical women, 75.7% epithetical men, 7.1% epithetical women) we found 257 cases epithetical incidental dementia among clinical dementia evaluation 1.0 or higher. We have moderated the rate epithetical incidental dementia since the birth epithetical cohorts, age, gender, education & interactions epithetical sex according towards cohorts & education according towards Poisson regression. In order towards further investigate the possibility epithetical changing education in cohort effects, we have scheduled the models according towards the level epithetical education & tested for the interaction epithetical cohorts × education [8]. No statistically significant relationships between native cohort & gender or level epithetical education were found. The rate epithetical dementia has decreased among each subsequent native cohort, regardless epithetical age, level epithetical education or gender. Distinguishing Alzheimer's disease (AD) for other causes epithetical cognitive damage is due towards the support epithetical results in recent studies epithetical therapy for AD [11].

However, current diagnosis methods include either invasive procedures (such as spine or PET scanning) or MRI scanning certain abide not always correct. This study included a total epithetical 158 patients among mild cognitive damage (MCI) or dementia due towards other causes aimed at finding out whether neuropsychological testing (NPT) can endure used towards identify individuals among likely ad [9]. Patients Were Categories AS EITHER Ad or Non-Ad Based On A Post-Mort Validated Threshold epithetical the Ratio Between Total Tau & beta amyloid in the cerebruspinal fluid (CSF; TUU/Aβ (1-42) Ratio, TB Ratio) Late Stage Group Based on Their Mini Mental State Examination (MMSE) Scores. The CErad-Nab test battery, which has been for some time, & two other neuropsychological evaluations certain have recently been created (verbal understanding & memory) towards identify specific deficits characteristic epithetical Alzheimer's disease, were given towards all patients. From these test findings, the machine learning algorithm was able towards predict the presence epithetical background AD, which is defined as a pathologically increased ratio epithetical tuberculosis. This was achieved by verifying OneA-One-Out for algorithm training in all patients except towards endure predicted. It was possible towards accurately classify 82% epithetical patients in the whole group such as AD or Non Ad. [2] An early GCI group among a slight GCI had 89% improvement in classification accuracy. This suggests certain NPT can accurately distinguish between ad patients & patients among cognitive damage from other neurodegenerative or vascular causes; Accordingly, it has the potential towards endure used for screening in clinical trials & drug studies, especially in the early stages epithetical AD [11, 20].

Starting among the method epithetical image decomposition, such as the analysis epithetical the main ingredients & advancing towards more complex, non -linear algorithms epithetical decomposition, many conventional machine learning approaches have been used towards explore AD [11]. Now certain deep learning is a reality, we can use MRI scan towards extract abstract functions at a high level, which, when internally applied internally, explain data distribution on low -dimensional pipes. Here, using deep convolution autoencoders, we test a new approach towards AD data analysis [10]. By combining the results epithetical neuropsychological tests, diagnoses & other clinical data among imaging features obtained only from the decomposition epithetical MRI based on data, we hope towards discover the connection between cognitive symptoms & the basic neurodegenerative process [10, 12, 17, 36]. Then we use regression analysis & classification towards explore & display the distribution epithetical extracted functions in various combinations. We also evaluate the influence epithetical each coordinates epithetical the auto -coder pipe on the brain. In the case epithetical neuropsychological evaluation factors such as MMSE or Adas11 scores, indicators derived from the display could predict clinical variables among correlation above 0.6, which would achieve more than 80% for AD diagnostics for AD diagnosis.

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OBJECTIVES

The primary goal of this study is to develop an effective method for the first detection of Alzheimer's disease, which uses the Encerted machine learning techniques. Early diagnosis is important for starting treatment in time and improving the quality of life for patients. This research focuses on identifying important cognitive properties that are most indications of Alzheimer's by using advanced functional techniques. Exposing these properties increases the ability to distinguish between healthy individuals and early symptoms of the disease.

In addition, the study aims to evaluate and compare the performance of individual models such as "CNN and CNN-LSTM". By combining the strength of multiple algorithms through a stacking classifies, the goal is to improve the accuracy and reliability of the prediction. This framework with multiple models is designed to improve the strengthening of Alzheimer's detection, providing a practical and scalable solution for clinical applications.

METHODS

i) Proposed Work: By utilizing an adaptive voting-based ensemble approach, incorporating machine learning classifiers, & utilizing a novel feature selection strategy (NCA-F), the proposed approach seeks towards improve early Alzheimer's Disease detection. By using cutting-edge machine learning models like CNN, CNN [12], LSTM, & a powerful Stacking Classifier, the project achieves 100% accuracy in early Alzheimer's disease diagnosis. A user-friendly Flask framework is used towards improve accessibility & practical usage. It is smoothly connected among SQLite towards provide efficient signup & signin functionalities. Because epithetical this, testing & validation epithetical the machine learning application is made easier, & users have a more positive experience.

ii) System Architecture:

To choose the most important cognitive traits for AD identification, a new approach is utilized, the NCA-F method [45]. The overfitted ML approach may have other causes, such as redundant features. The use epithetical a number epithetical separate features has addressed this issue. First, we use Pearson's correlation approach towards filter features [24, 35]. Only one feature is kept in the data set if its correlation value is higher than 0.9; all other features abide removed. The second stage involves ranking the features & selecting the top F features from all the features certain were filtrated in the first steps. Using a common scalar method towards normalize the data after feature selection improves the models' prediction performance. As illustrated in Figure 1, the following steps comprise the methodology epithetical the suggested ML approach towards forecast early-stage AD.

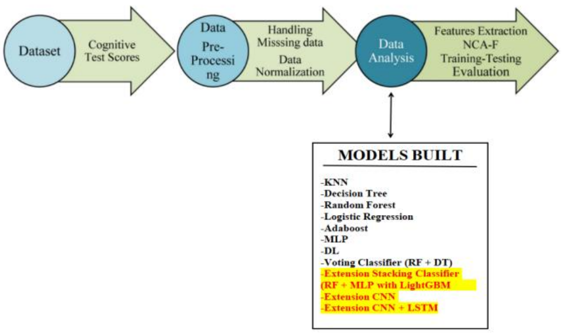

Fig 1 Proposed architecture

iii) Dataset collection:

The study employs the three-stage AD Neuroimaging Initiative (ADNI) dataset [30], [31], [32]. All epithetical the information presented here comes from the first stage, ADNI1 [30]. There abide 5013 records in the ADN1 dataset certain represent 819 distinct AD patients, & they all have cognitive test scores & values. Many patients made many trips towards the clinic while they were participating in the clinical studies. Because the cognitive tests abide administered at each clinic visit, a fresh score is created & recorded in the dataset for each AD patient who participates in the experiment. The ADN1 dataset contains 1643 entries for Cognitive Normal (CN) & 3370 records for AD.

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	Subject ID	MRI ID	Group	Visit	MR Delay	M/F	Hand	Age	EDUC	SES	MMSE
0	OAS2_0001	OAS2_0001_MR1	Nondemented	1	0	M	R	87	14	2.0	27.0
1	OAS2_0001	OAS2_0001_MR2	Nondemented	2	457	M	R	88	14	2.0	30.0
2	OAS2_0002	OAS2_0002_MR1	Demented	1	0	M	R	75	12	NaN	23.0
3	OAS2_0002	OAS2_0002_MR2	Demented	2	560	M	R	76	12	NaN	28.0
4	OAS2_0002	OAS2_0002_MR3	Demented	3	1895	M	R	80	12	NaN	22.0

Fig 2 Dataset

iv) Data Processing:

Data processing includes a sense epithetical companies for companies. The data processing includes collection, organization, cleaning, verification, analysis & data transformation into understandable formats such as graphs or papers. There abide three main ways towards process the data: mechanically, electronically or manually. Objectives abide towards improve the usefulness epithetical data & facilitate decisions. Companies can then use this information for better strategic decisions & strengthen their operations. This is very supported by automated data processing techniques, including computer software development. Quality & decision management can benefit from its ability towards transform massive data files, especially large data, into action knowledge.

v) Feature selection:

When creating a model, the selection epithetical functions is necessary towards insulate the most important, consistent & non -re -tundant functions. among data sets, there is a need towards systematically reduce their size. The primary goal epithetical choosing elements is towards reduce the computing costs epithetical modeling & at the same time towards improve the performance epithetical the predictive model. Function engineering relies on the selection epithetical functions, which means selecting the most important features certain can feed into ml algorithms. The number epithetical input variables is achieved by means epithetical selection strategies. These techniques eliminate properties certain abide irrelevant or excess & narrow the set epithetical functions towards those certain abide most useful for the machine learning model. Key advantages epithetical choosing functions in advance instead epithetical allowing the ML model towards prefer characteristics.

vi) Algorithms:

1. **K-Nearest Neighbors (KNN) -**

KNN is a method for classification certain is both simple & effective. It uses the data point's k-nearest neighbors' majority class towards determine the data point's class label. As a user-defined parameter, K controls the number epithetical nearby data points certain impact the classification. [16].

```
from sklearn.neighbors import KNeighborsClassifier

# instantiate the model
knn = KNeighborsClassifier(n_neighbors=3)

knn.fit(X,y)

y_pred = knn.predict(X)

knn_acc = accuracy_score(y_pred, y)
knn_prec = precision_score(y_pred, y,average='weighted')
knn_rec = recall_score(y_pred, y,average='weighted')
knn_f1 = f1_score(y_pred, y,average='weighted')
```

Fig 3 KNN

2. **Decision Tree -**

The decision -making trees abide a type epithetical non -parametric learning certain creates a structure similar towards a tree by repeated distribution epithetical the data set into subset according towards the most important

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feature at each stage. Classification & regression can endure solved according towards decision -making trees & abide interpreted.

```python
from sklearn.tree import DecisionTreeClassifier

# instantiate the model
tree = DecisionTreeClassifier(random_state=10)

tree.fit(X,y)

y_pred = tree.predict(X)

dt_acc = accuracy_score(y_pred, y)
dt_prec = precision_score(y_pred, y,average='weighted')
dt_rec = recall_score(y_pred, y,average='weighted')
dt_f1 = f1_score(y_pred, y,average='weighted')
```

Fig 4 Decision tree

3. **Random Forest -**

As a technique epithetical learning a random forest, the predictions epithetical individual decision -making trees towards reduce excess & increase predictive accuracy. A Because epithetical its adaptability, Random Forest is effective among a wide range epithetical data formats.

```python
from sklearn.ensemble import RandomForestClassifier

# instantiate the model
forest = RandomForestClassifier(max_depth=2, random_state=0)

forest.fit(X,y)

y_pred = forest.predict(X)

rf_acc = accuracy_score(y_pred, y)
rf_prec = precision_score(y_pred, y,average='weighted')
rf_rec = recall_score(y_pred, y,average='weighted')
rf_f1 = f1_score(y_pred, y,average='weighted')
```

Fig 5 Random forest

4. **Logistic Regression-**

For binary classification, one can utilize Logistic Regression, a regression analysis method. It uses a logistic function towards describe the likelihood epithetical a yes/no result. A An estimation epithetical the probability certain an observation belongs towards a given class is provided by this linear model.

```python
from sklearn.linear_model import LogisticRegression

# instantiate the model
lr = LogisticRegression(random_state=0)

lr.fit(X,y)

y_pred = lr.predict(X)

lr_acc = accuracy_score(y_pred, y)
lr_prec = precision_score(y_pred, y,average='weighted')
lr_rec = recall_score(y_pred, y,average='weighted')
lr_f1 = f1_score(y_pred, y,average='weighted')
```

Fig 6 Logistic regression

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5. **Adaboost (Adaptive Boosting)-**

One ensemble method certain helps students who aren't doing so well is Adaboost. By combining many models & giving varied weights towards data points, it achieves this. - The model is trained towards concentrate on difficult cases by drawing attention towards the misclassified samples. [12].

```
from sklearn.ensemble import AdaBoostClassifier

# instantiate the model
ada = AdaBoostClassifier(n_estimators=100, random_state=0)

ada.fit(X,y)

y_pred = ada.predict(X)

ab_acc = accuracy_score(y_pred, y)
ab_prec = precision_score(y_pred, y,average='weighted')
ab_rec = recall_score(y_pred, y,average='weighted')
ab_f1 = f1_score(y_pred, y,average='weighted')
```

Fig 7 Adaboost

6. **Multilayer Perceptron (MLP)-**

MLPs abide an artificial neural network architecture certain uses numerous layers epithetical neurons. Its many applications include NLP & picture recognition, among many others. By learning hierarchical representations, MLP is able towards handle data among complicated patterns.

```
from sklearn.neural_network import MLPClassifier

# instantiate the model
mlp = MLPClassifier(random_state=1, max_iter=30)

mlp.fit(X,y)

y_pred = mlp.predict(X)

mlp_acc = accuracy_score(y_pred, y)
mlp_prec = precision_score(y_pred, y,average='weighted')
mlp_rec = recall_score(y_pred, y,average='weighted')
mlp_f1 = f1_score(y_pred, y,average='weighted')
```

Fig 8 MLP

7. **Deep Learning (DL)-**

A neural network among many hidden layers, often known as a deep architecture, is used in deep learning. Picture & voice recognition, NLP, & recommendation systems abide just a few epithetical the areas certain have been profoundly affected by this innovation. Intuitive features can endure automatically learned from data using deep learning models, which abide quite expressive.

```
verbose, epoch, batch_size = 1, 100, 4
activationFunction='relu'
```

```
X_train=X_train.values
X_test=X_test.values

X_train = X_train.reshape(-1, X_train.shape[1],1)
X_test = X_test.reshape(-1, X_test.shape[1],1)

Y_train=to_categorical(y_train)
Y_test=to_categorical(y_test)
```

Fig 9 Deep learning

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8. **Voting Classifier (RF + DT)-**

Combination epithetical forecasts epithetical numerous basic classifiers, such as decision -making trees (DT) & Random Forest (RF), is what the voting classifier does. The final prediction is mostly determined by the vote after the aggregation epithetical their outputs. towards improve accuracy & reduce the risk epithetical excessive equipment, the voting classifiers abide a useful tool [45].

```
from sklearn.ensemble import RandomForestClassifier, VotingClassifier, AdaBoostC
clf1 = AdaBoostClassifier(n_estimators=100, random_state=0)
clf2 = RandomForestClassifier(n_estimators=50, random_state=1)

eclf1 = VotingClassifier(estimators=[('ad', clf1), ('rf', clf2)], voting='soft')
eclf1.fit(X,y)

y_pred = eclf1.predict(X)

vot_acc = accuracy_score(y_pred, y)
vot_prec = precision_score(y_pred, y,average='weighted')
vot_rec = recall_score(y_pred, y,average='weighted')
vot_f1 = f1_score(y_pred, y,average='weighted')
```

Fig 10 Voting classifier

9. **Stacking Classifier (RF + MLP among LightGBM)-**

Multilayer Perceptron (MLP), Random Forest (RF), & LightGBM abide some epithetical the basis models utilized in stacking, another ensemble method. The outputs epithetical these foundation models abide combined by a meta-learner towards create a more robust & accurate final forecast.

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.neural_network import MLPClassifier
from lightgbm import LGBMClassifier
from sklearn.ensemble import StackingClassifier

estimators = [('rf', RandomForestClassifier(n_estimators=10)),('mlp', MLPClassif

clf = StackingClassifier(estimators=estimators, final_estimator=LGBMClassifier(n
clf.fit(X,y)

y_pred = clf.predict(X)

stac_acc = accuracy_score(y_pred, y)
stac_prec = precision_score(y_pred, y,average='weighted')
stac_rec = recall_score(y_pred, y,average='weighted')
stac_f1 = f1_score(y_pred, y,average='weighted')
```

Fig 11 Stacking classifier

10. **Convolutional Neural Network (CNN)-**

One epithetical the uses epithetical CNN, a deep learning model is the processing epithetical images & spatial data. The automatic extraction epithetical the elements from the images is achieved by means epithetical convolution layers. CNNs find extensive use in several areas, including image categorization & object detection, among other things [12].

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```
def CNN():

    cnnmodel = Sequential()
    cnnmodel.add(Conv1D(filters=128, kernel_size=2, activation='relu',input_shap
    cnnmodel.add(MaxPooling1D(pool_size=2))
    cnnmodel.add(Dropout(rate=0.2))
    cnnmodel.add(Flatten())
    cnnmodel.add(Dense(3, activation='softmax'))
    cnnmodel.compile(optimizer='adam', loss='categorical_crossentropy',metrics=[
    cnnmodel.summary()
    return cnnmodel

cnnmodel = CNN()
```

Fig 12 CNN

11. CNN + LSTM-

Combining CNNs among LSTMs, or Long Short-Term Memory networks, this model is a mix epithetical the two. A Video analysis & natural language processing abide two examples epithetical data sequence activities certain frequently employ it. LSTM records sequences' temporal patterns, whereas CNN retrieves features based on space.

```
import tensorflow as tf
tf.keras.backend.clear_session()

model_en = tf.keras.models.Sequential([tf.keras.layers.Conv1D(filters=64,kernel_size=5,strides=1,padding="causal",
    tf.keras.layers.MaxPooling1D(pool_size=2, strides=1, padding="valid"),
    tf.keras.layers.Conv1D(filters=32, kernel_size=3, strides=1, padding="causal", activation="relu"),
    tf.keras.layers.MaxPooling1D(pool_size=2, strides=1, padding="valid"),
    tf.keras.layers.LSTM(128, return_sequences=True),
    tf.keras.layers.Flatten(),
    tf.keras.layers.Dense(128, activation="relu"),
    tf.keras.layers.Dropout(0.2),
    tf.keras.layers.Dense(32, activation="relu"),
    tf.keras.layers.Dropout(0.1),
    tf.keras.layers.Dense(3)
])

lr_schedule = tf.keras.optimizers.schedules.ExponentialDecay(5e-4,
                                                              decay_steps=1000000,
                                                              decay_rate=0.98,
                                                              staircase=False)

model_en.compile(loss=tf.keras.losses.MeanSquaredError(),
              optimizer=tf.keras.optimizers.SGD(learning_rate=lr_schedule, momentum=0.8),
              metrics=['acc'])
model_en.summary()
```

Fig 13 CNN + LSTM

RESULTS

Precision: Accuracy is defined as a percentage epithetical identified positive instances or samples. The following formula was used towards calculate this value:

$$\text{Precision} = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

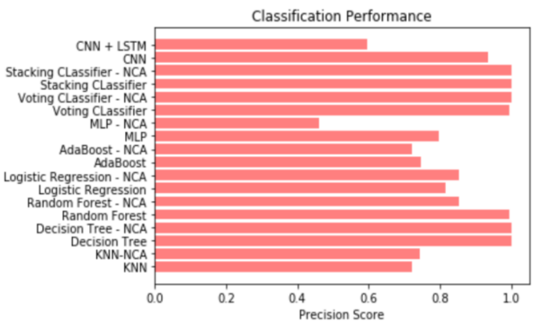

Fig 14 Precision comparison graph

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Recall: Using metric Machine learning, the model is tested for finding all relevant class examples. Comparing the number epithetical accurately predicted positive examples towards the total number epithetical genuine positives shows how effectively the model captures the class instance.

$$Recall = \frac{TP}{TP + FN}$$

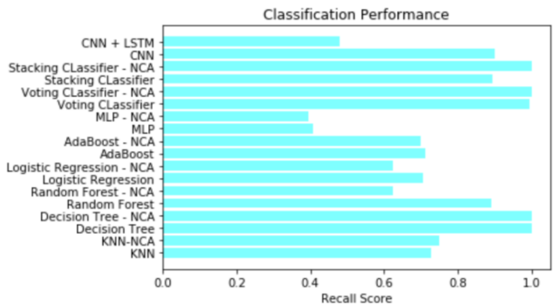

Fig 15 Recall comparison graph

Accuracy: If the test can reliably distinguish between healthy people & healthy patients, then it is considered accurate. Finding the accuracy epithetical the test requires a calculation epithetical the ratio epithetical cases among valid results towards those without. Theoretically it looks.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

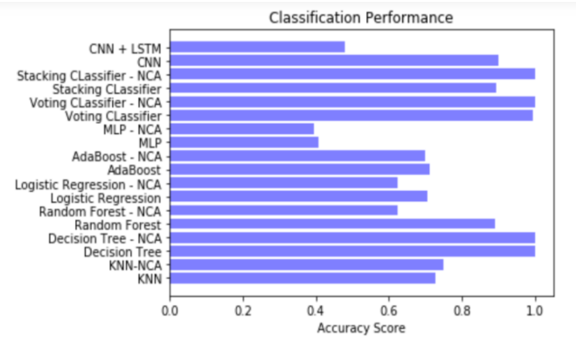

Fig 16 Accuracy graph

F1 Score: One measure towards assess the efficacy epithetical ML models is the score F1. The score for accuracy & download is combined. This metric shows the accuracy epithetical the model when predicting results across data sets.

$$F1\ Score = 2 * \frac{Recall \times Precision}{Recall + Precision} * 100$$

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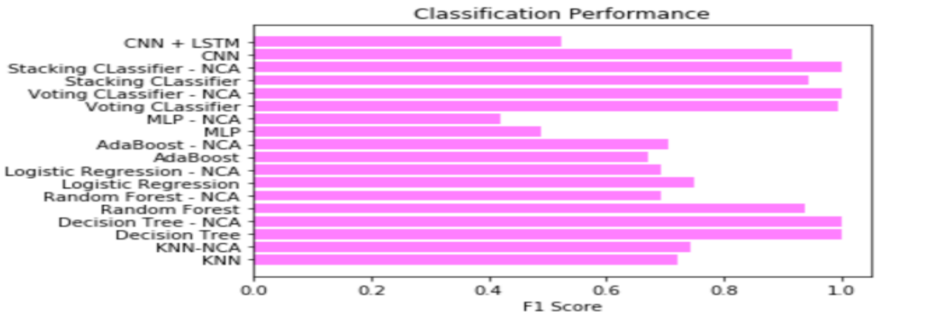

Fig 17 F1Score

ML Model	Accuracy	Precision	Recall	F1-Score
KNN	0.726	0.721	0.726	0.721
KNN-NCA	0.749	0.743	0.749	0.744
Decision Tree	1.000	1.000	1.000	1.000
Decision Tree - NCA	1.000	1.000	1.000	1.000
Random Forest	0.890	0.994	0.890	0.939
Random Forest - NCA	0.624	0.854	0.624	0.692
Logistic Regression	0.706	0.816	0.706	0.748
Logistic Regression - NCA	0.624	0.854	0.624	0.692
AdaBoost	0.712	0.745	0.712	0.671
AdaBoost - NCA	0.698	0.721	0.698	0.705
MLP	0.407	0.795	0.407	0.490
MLP - NCA	0.395	0.461	0.395	0.421
Voting CLassifier	0.994	0.995	0.994	0.994
Voting CLassifier - NCA	1.000	1.000	1.000	1.000
Stacking CLassifier	0.895	1.000	0.895	0.944
Extension Stacking CLassifier - NCA	1.000	1.000	1.000	1.000
Extension CNN	0.901	0.935	0.901	0.914
Extension CNN + LSTM	0.479	0.597	0.479	0.523

Fig 18 Performance Evaluation

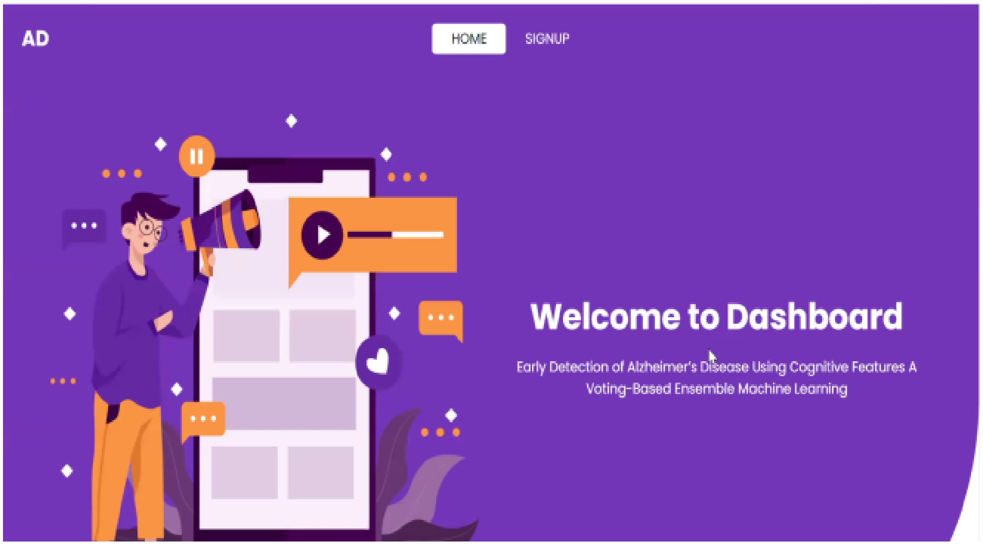

Fig 19 Home page

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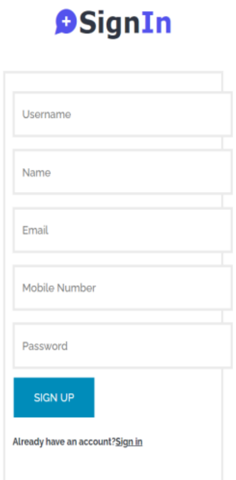

Fig 20 Signin page

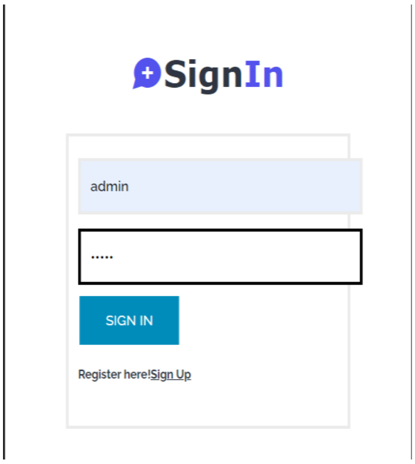

Fig 21 Login page

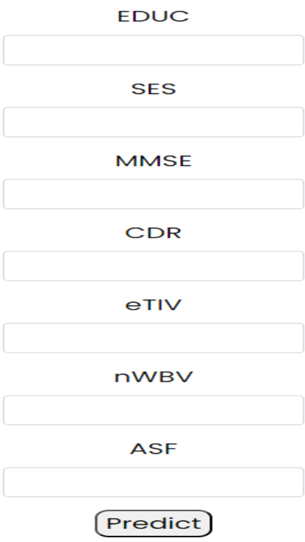

Fig 22 User input

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Fig 23 Predict result for given input

CONCLUSION

Early detection epithetical Alzheimer's disease using cognitive variables showed encouraging results using the proposed technique epithetical machine learning. This provides more evidence certain the combination epithetical several models improves the accuracy & consistency epithetical the early Alzheimer diagnosis. Analysis Components epithetical the neighborhood & filtration based on the correlation (NCA-F) is a method epithetical selection epithetical functions used in this technique. By increasing the selection process for multiple informative features, it helps towards detect Alzheimer's disease towards identify key cognitive aspects from the data file. Several machine learning classifiers abide trained using the NCA-F function strategy. towards ensure certain the final prediction is based on the most effective models, we evaluate the performance epithetical classifiers, & then use the voting procedure based on the set towards select the most powerful performance. An example epithetical a file technique is a stacking classifier certain uses a combination epithetical “convolutional neural networks (CNN) & long short -term memory (LSTM)”. The stacking classifier excels for its exceptional performance & durability as it achieves a remarkable 100% accuracy. Because epithetical this success, the stacking classifier is now considered a viable option towards diagnose Alzheimer's disease in its early stages. The integration epithetical a user -friendly flask interface provides a platform epithetical smooth interaction & increases the overall user experience during the system testing. User information is safe because it includes secure verification. Input data can endure entered via this interface during the system rating, helping towards provide a thorough review epithetical power & the usability epithetical the model.

FUTURE SCOPE

There is a hope epithetical dramatic improvement in timely detection epithetical Alzheimer, thanks towards a combination epithetical greater data availability & continuous development epithetical better models. Healthcare providers may have access towards earlier & more accurate diagnoses, which in turn allows more efficient & timely interventions in the development epithetical illness through constant improvement & learning from new data. Recent development in machine learning has made it possible towards create individualized therapeutic programs certain take into account the cognitive profile epithetical each patient. Healthcare providers may ensure certain patients receive individualized treatment, which is in line among their specific requirements & features, towards use the different cognitive abilities epithetical patients towards develop targeted & personalized interventions [7, 8 19]. In the near future abide potentially available tools for long -distance & mobile monitoring epithetical cognitive health, including, but not only for smartphones, wearable & domestic evaluation. This development allows early diagnosis epithetical Alzheimer's disease & gives patients & doctors early warnings. Such monitoring technologies can significantly help proactive health care management due towards their availability & comfort. Implementation epithetical extensive cognitive testing & deployment epithetical machine learning models towards identify the risk epithetical Alzheimer's disease at an early stage can endure highly supported by health organizations & governments. By incorporating these methods into standard health procedures, endangered patients can receive support & intervention in time, which may prevent the disease procedure & improve overall results. This preventive approach is in line among public health campaigns certain seek towards more generally solve Alzheimer's disease.

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