Alzheimer’s Disease Prediction using Traditional ML Algorithms on Cross – Sectional MRI Images

Abstract

Alzheimer's disease (AD) is the most common cause of dementia in older adults, impacting millions of people around the world. With the growing number of cases globally, there is a rising interest in using machine learning techniques to help detect diseases like Alzheimer's early. In Alzheimer's, the brain experiences progressive damage, leading to memory loss and cognitive decline. As the global population ages, the social, financial, and emotional burden on families, healthcare systems, and communities continues to rise. Detecting Alzheimer's early is critical because treatments are more effective when started before the disease advances too far. This study focuses on improving early detection of Alzheimer's by analyzing cross-sectional imaging MRI data and clinical information. We employed machine learning techniques such as Random Forest, Support Vector Machine (SVM), Convolutional Neural Networks (CNN) and XGBoost to find the best approach for predicting Alzheimer's disease. Using the Open Access Series of Imaging Studies (OASIS-1) dataset, we evaluated model performance through key metrics like Precision, Recall, Accuracy, and F1-score. The Random Forest model achieved an accuracy of 90%, while the XGBoost model showed perfect accuracy at 100%. These results highlight the potential of advanced machine learning models, combined with imaging data, to identify early stages of Alzheimer's disease, enabling earlier diagnosis and improving the chances for effective treatment.

Keywords

Alzheimer's Disease (AD), Early Detection, Cross-Sectional Imaging, Machine Learning, MRI Imaging, Random Forest, XGBoost, Convolutional Neural Networks (CNN), Support Vector Machine (SVM), OASIS-1 Dataset, Cognitive Decline, Dementia, Predictive Modeling, Neuroimaging, Clinical Data, Disease Diagnosis.

Introduction

Alzheimer's Disease (AD) is a progressive neurodegenerative disorder and the leading cause of dementia, affecting millions of people globally. It primarily impacts memory, thinking, and behavior, with symptoms that worsen over time. Early signs often include memory loss and difficulty in completing familiar tasks, which can advance to severe cognitive and functional impairments. While typically diagnosed in individuals aged 65 and older, changes in the brain can begin years before symptoms become evident. Alzheimer's is characterized by the buildup of amyloid plaques and tau tangles, which lead to neuron death and brain tissue loss. Although no cure exists, early detection and intervention are crucial for managing symptoms and improving the quality of life for those affected. Research continues to seek effective treatments and diagnostic tools to facilitate early detection.

Recent advancements in machine learning and neuroimaging have provided promising approaches for the early diagnosis of Alzheimer's Disease. This study utilizes the Open Access Series of Imaging Studies (OASIS-1) dataset, which contains 390 MRI cross-sectional images and corresponding clinical data. Specifically, we focused on a processed file featuring subj_111 and T88_111 to develop predictive models aimed at identifying early signs of Alzheimer's.

In our analysis, we implemented several machine learning algorithms: Random Forest, XGBoost, Support Vector Machine (SVM), and Convolutional Neural Networks (CNN). Each model was trained on the MRI and clinical datasets to evaluate its predictive capability.

Random Forest is an ensemble learning method that constructs multiple decision trees during training, aggregating their predictions to improve accuracy and robustness. It works by randomly selecting subsets of the data and features at each tree node, thereby reducing overfitting and enhancing model performance.

XGBoost (Extreme Gradient Boosting) is a highly efficient implementation of the gradient boosting framework. It builds trees sequentially, with each new tree focusing on correcting errors from the previous ones. XGBoost incorporates techniques such as regularization and tree pruning, optimizing performance and preventing overfitting, making it particularly effective for classification tasks.

Support Vector Machine (SVM) is a supervised learning algorithm that identifies the optimal hyperplane for separating different classes in high-dimensional spaces. SVM is well-suited for classification tasks and can handle both linear and non-linear data through kernel functions.

Convolutional Neural Networks (CNN) are specialized deep learning models designed for image processing tasks. They use convolutional layers to extract features from images, followed by pooling layers to reduce dimensionality. CNNs are particularly effective for tasks involving visual data, like MRI scans.

Among these models, Random Forest achieved an accuracy of 90%, while XGBoost demonstrated superior performance with a perfect accuracy of 100%. Although SVM and CNN were also employed, they produced lower accuracy in comparison.
These results indicate that machine learning algorithms, especially XGBoost and Random Forest, can significantly enhance the early detection of Alzheimer's Disease, potentially leading to timely interventions and improved management of the condition.

Literature Review

Abdelwahab et al. [1] conducted a pivotal study that addressed the challenges associated with high-dimensional microarray data and limited sample sizes. They implemented Principal Component Analysis (PCA) and Singular Value Decomposition (SVD) for gene selection, significantly reducing dimensionality prior to classification. Utilizing a seven-layer Convolutional Neural Network (CNN), their models, PCA-CNN and SVD-CNN, demonstrated remarkable performance, achieving accuracies of 96.60% and 97.08%, respectively. The evaluation process employed cross-entropy loss, and the models were optimized using the ADAM optimizer. Additionally, to mitigate the risk of overfitting, data augmentation techniques—such as rotations and zooms—were incorporated. This research underscores the potential of integrating advanced gene selection methods with CNN architectures, paving the way for improved early diagnosis of AD and suggesting a robust framework for predicting neurodegenerative disorders. The authors also advocate for further investigations into alternative gene selection techniques and deep learning models to enhance predictive capabilities in this field.

Alzheimer's disease (AD) remains the predominant cause of dementia among the elderly, presenting substantial health, social, and economic challenges. Early diagnosis is crucial for timely intervention and better health outcomes. **Kavitha et al. [2]** conducted a thorough evaluation of various machine learning algorithms, including Decision Trees, Random Forests, Support Vector Machines, Gradient Boosting, and Voting classifiers, utilizing the OASIS dataset. The study employed performance metrics such as Precision, Recall, Accuracy, and F1-score, with the leading model achieving an accuracy of 83% on the test data. These findings underscore the promise of machine learning techniques in facilitating early AD diagnosis. Future research is planned to focus on feature extraction, elimination of redundancies, and integration of metrics such as the Mini-Mental State Examination (MMSE) and educational levels to further enhance model performance and effectively differentiate between healthy individuals and those diagnosed with AD.

As the aging demographic continues to grow, the repercussions of AD increasingly affect social, financial, and healthcare systems. **Uddin et al. [3]** explored the early diagnosis of AD through various machine learning models, including Gaussian Naive Bayes (GaussianNB), Decision Trees, Random Forests, XGBoost, Voting Classifier, and Gradient Boosting. These models were trained on the Open Access Series of Imaging Studies (OASIS) dataset and assessed based on accuracy, precision, recall, and F1 score. Remarkably, the Voting Classifier achieved the highest validation accuracy of 96%. The findings underscore the potential of these machine learning techniques to facilitate early diagnosis, which could significantly reduce mortality rates and enhance patient outcomes, especially in light of the absence of a cure for AD. The study emphasizes the critical need for early detection, with future research aimed at improving model accuracy through refined feature selection, elimination of redundant features, and the extraction of new features to better identify AD in its initial stages.

This paper examines the role of machine learning (ML) techniques in the early detection of Alzheimer's disease (AD), a neurocognitive disorder characterized by memory loss, behavioral changes, and language difficulties. Early diagnosis is essential for effective treatment. **Patil et al. [4]** focus on various ML methods utilizing the Alzheimer's Disease Neuroimaging Initiative

(ADNI) dataset, addressing key topics such as dataset characteristics, evaluation metrics, and model performance. Their analysis compares two models: an 18-layer convolutional neural network (CNN) and a 3D CNN, revealing that the 18-layer CNN significantly outperforms the latter, achieving an impressive accuracy of 98%. The findings indicate that ML methods can surpass traditional statistical approaches, with reported accuracies ranging from 80% to 98%. However, a notable limitation identified in the study is the models' inability to classify the different stages of AD. The research emphasizes the effectiveness of deep CNNs with more than 15 layers and suggests that incorporating voting classifiers may further enhance diagnostic accuracy in clinical applications.

This study investigates the application of machine learning (ML) techniques for predicting Alzheimer's disease (AD) using the OASIS-2 dataset, which comprises data from 150 individuals aged between 60 and 96. **Alshamlan et al. [5]** compared several ML models, including Support Vector Machines, Random Forests, and Logistic Regression, while employing feature selection methods such as Minimum Redundancy Maximum Relevance (mRMR) and Mutual Information (MI). Their findings indicated that Logistic Regression, in conjunction with mRMR, achieved the highest accuracy of 99.08%. Although mRMR and the correlation coefficient yielded similar outcomes, MI displayed slight discrepancies. The performance of Logistic Regression and Support Vector Machines was comparable, while the Random Forest model demonstrated lower accuracy. The study also highlighted the sensitivity of the 70-30 split methodology to outliers, noting that their removal improved model performance, whereas k-fold validation was less affected by such outliers. Overall, this research emphasizes the vital importance of feature selection in enhancing model efficiency. Future work aims to explore advanced feature selection techniques, utilize larger datasets, and incorporate additional ML algorithms to further improve prediction accuracy, with the goal of enhancing diagnostic tools for early AD detection for individuals and their families.

Rallabandi and Seetharaman [6] analyzed data from 117 individuals aged 60 to 96 years, which included 33 HC, 27 PD, 30 MCI, and 27 AD participants. The classification process involved 3D tissue segmentation of white matter (WM), gray matter (GM), and cerebrospinal fluid (CSF) utilizing the FSL tool. The researchers computed surface fractal dimensions through 3D box-counting techniques, while gray matter density (GMD) and the local gyrification index (LGI) were estimated using FreeSurfer's anatomical lobar parcellation. The indices were trained on two-thirds of the dataset and evaluated on the remaining third with various machine learning classifiers. Notably, Naïve Bayes and Support Vector Machine (SVM) classifiers achieved the highest classification accuracy of 78% during 5-fold cross-validation. While this method demonstrates promise for dementia classification with lower computational costs, the small sample size poses limitations on overall performance. Future research will focus on exploring deep learning techniques, including convolutional and recurrent neural networks, to improve accuracy with larger datasets.

This paper explores the efficacy of various machine learning algorithms for the early detection of Alzheimer's disease (AD) utilizing a dataset of 6,400 pre-processed MRI images. **Bharath M et al. [7]** evaluated key models, including Support Vector Machines (SVM), Linear Discriminant Analysis (LDA), Principal Component Analysis (PCA), and Convolutional Neural Networks (CNN) employing the EfficientNetB0 architecture. Among these, the SVM with a linear kernel achieved the highest performance, boasting an impressive accuracy of 98% for detection and 98.7% for classification, thus outperforming other SVM variants. Specifically, SVM models utilizing polynomial and radial basis function (RBF) kernels

achieved accuracies of 86% and 83%, respectively, while LDA recorded a notable accuracy of 90%. The PCA analysis indicated that 175 components were necessary to achieve 80% accuracy. CNN models yielded varied results; VGG16 underperformed, achieving only 50% accuracy, likely due to issues related to RGB image conversion, whereas the EfficientNetB0 model showed improvement, reaching an accuracy of 83% following image resizing. The findings highlight the superiority of SVM with linear kernels for AD prediction and suggest avenues for enhancing the performance of CNN models in future research.

The early diagnosis of Alzheimer's disease (AD) is becoming increasingly important in light of the growing aging population. **Jiang et al. [8]** emphasize the challenge of late diagnoses, noting that 67% of patients are identified only at intermediate stages, thereby missing crucial intervention opportunities. To enhance early detection, the researchers categorize mild cognitive impairment (MCI) into three distinct subtypes, including subjective memory complaints (SMC). They developed a clustering model that integrates neural networks with K-Nearest Neighbors (KNN) and trained it using MATLAB, achieving an impressive test accuracy of 90% for intelligent MCI diagnosis. Furthermore, they proposed an enhanced Long Short-Term Memory (LSTM) neural network that incorporates attention mechanisms to predict disease progression through multiple clinical assessments, reaching a test accuracy of 88%. This research significantly improves the diagnostic framework for AD, providing accurate classifications and a time-series-based model to assess disease progression. These advancements offer substantial contributions to the field of Alzheimer's research and diagnosis, supporting strategies for earlier interventions.

Kolte et al. [9] explore the early detection of Alzheimer's disease (AD) through the application of various machine learning (ML) algorithms, identifying the random forest (RF) algorithm as the most effective method, achieving an impressive accuracy of 93.69%. Given that AD is a progressive neurological disorder that often remains undetected in its early stages, timely identification is essential for effective intervention and treatment strategies. The researchers compared multiple ML models, including logistic regression (64.86%), Naive Bayes (88.29%), support vector machine (SVM) (91.89%), decision tree (83.79%), and random forest, with RF outperforming the others based on features derived from a correlation matrix. Additionally, a graphical user interface (GUI) was developed using Flask for the backend, along with HTML, CSS, and Bootstrap for the frontend, enabling users to input parameters and receive categorized results (Converted, Demented, Non-Demented). The study recognizes certain limitations, such as the exclusion of external factors like family history and genetics, and suggests that future research could enhance model performance by integrating these variables, as well as incorporating features such as a recommendation system and tracking patient medical history.

Diwate et al. [10] investigate the application of machine learning (ML) techniques for predicting dementia by utilizing social and biological data from the OASIS dataset, intentionally excluding brain MRI images. The study tackles several data challenges, including the management of missing values through median replacement and the normalization of data to minimize computational demands. Among the key models evaluated, the Multilayer Perceptron (MLP) and Decision Tree achieved commendable results, with an accuracy of 83.9% and recall scores of 0.836 and 0.800, respectively. Feature selection was executed using a correlation heatmap, supplemented by graphical analyses to explore variable relationships. While models like SVM and Naive Bayes exhibited lower recall rates, the MLP emerged as the preferred model due to its balanced performance in both accuracy and recall, alongside a stable ROC score. This research underscores the critical role of Clinical Dementia Rating in

facilitating early diagnosis and advocates for the implementation of these models in clinical settings to enhance dementia detection and prevention. The paper concludes by emphasizing the need for further research aimed at developing a cost-effective and efficient system for early diagnosis and treatment.

Proposed Work

The primary objective of this study is to develop an effective and reliable method for the early detection of Alzheimer's Disease (AD) using machine learning techniques by leveraging both clinical data and MRI cross-sectional image data from the OASIS-1 dataset. This work focuses on integrating features extracted from clinical data and MRI images to classify patients as having dementia or no dementia, thereby facilitating early diagnosis and intervention.

Dataset Description

The OASIS-1 dataset comprises MRI cross-sectional images and associated clinical data for 416 individuals aged between 18 and 96. For this study, a subset of the data was used, specifically focusing on two groups of images, SUBJ_111 and T88_111, each consisting of **390 cross-sectional images**. The clinical dataset includes demographic, neuropsychological, and cognitive measurements, such as gender, age, education level, socioeconomic status (SES), Mini-Mental State Examination (MMSE), estimated Total Intracranial Volume (eTIV), normalized Whole Brain Volume (nWBV), and Atlas Scaling Factor (ASF), among others. These features are crucial for identifying patterns in cognitive decline associated with Alzheimer's Disease.

Data Preprocessing

In this study, data preprocessing is a critical step for handling missing values and preparing the data for machine learning models. For the clinical dataset, missing values in columns such as SES, MMSE, Clinical Dementia Rating (CDR), and Delay were imputed using the mean. The categorical variables like gender were encoded into numeric values, with male represented as 0 and female as 1. The clinical features were then standardized using *StandardScaler* to ensure uniformity across features, preventing any single feature from dominating the model due to scale differences. For the MRI image dataset, feature extraction was performed using a pre-trained *ResNet50* model from *Keras*, which was fine-tuned to extract relevant features from the cross-sectional MRI images. Both SUBJ_111 and T88_111 image datasets were used, and the features extracted from these images were concatenated with the clinical data to form a comprehensive feature set.

Feature Extraction and Integration

Clinical Data: After preprocessing the clinical data, we extracted relevant features such as Age, Education, SES, MMSE, eTIV, nWBV, ASF, and Delay. These features were scaled using StandardScaler.

Image Data: MRI images from the SUBJ_111 and T88_111 datasets were processed using ResNet50, a pre-trained deep learning model, which extracted 2048-dimensional feature vectors from each image. These features capture critical information related to brain structure,

which is essential for detecting atrophy associated with Alzheimer's Disease.

The extracted features from both clinical data and image data were then concatenated to form a unified feature set for classification. This combination of clinical and imaging data provides a holistic view of the patient, enabling more accurate prediction of Alzheimer's progression.

Model Development

For the classification task, multiple machine learning models were implemented to predict whether a patient had Alzheimer's Disease **(dementia)** or not **(no dementia)**. The following models were developed and evaluated:

Random Forest Classifier: A Random Forest classifier was trained on the combined feature set. This ensemble method was chosen for its ability to handle high-dimensional data and its robustness to overfitting. The model was trained on 80% of the dataset, and predictions were made on the remaining 20%. The model achieved high accuracy, with notable performance in detecting early stages of Alzheimer's Disease.

Support Vector Machine (SVM): An SVM with a linear kernel was employed to maximize the margin between the two classes (dementia vs. no dementia). The SVM model also demonstrated strong predictive power, particularly in separating patients with and without dementia based on the combined clinical and MRI features.

Convolutional Neural Network (CNN): A CNN model was implemented for image classification by using the extracted features from the MRI images. The network comprised convolutional layers, max-pooling layers, and dense layers, with Softmax output for classification. Although the image features were pre-extracted using ResNet50, the CNN was utilized to learn from these features and refine the classification process.

XGBoost: XGBoost, a gradient boosting algorithm, was trained on the combined dataset as well. XGBoost has been particularly effective in handling imbalanced datasets, making it a suitable choice for this problem where the number of dementia and non-dementia cases may differ. The model achieved excellent results, outperforming other models in terms of both accuracy and speed.

Evaluation Metrics

Each model was evaluated using several key performance metrics, including:

Accuracy: The percentage of correct predictions out of the total predictions.
Precision: The ratio of true positive predictions to the total number of positive predictions.
Recall (Sensitivity): The ratio of true positive predictions to the total number of actual positives.
F1-Score: The harmonic mean of precision and recall, providing a single metric that balances the two.
Confusion Matrix: A matrix displaying the true positive, false positive, true negative, and false negative predictions, which helped visualize the performance of the models.

The Random Forest model achieved an accuracy of 90%, while XGBoost demonstrated superior performance with an accuracy of 100%. The SVM model also performed well, with

an accuracy of around 92%, and the CNN achieved an accuracy of approximately 81%.

This proposed work demonstrates a comprehensive approach to the early detection of Alzheimer's Disease by combining clinical data and MRI images for feature extraction and classification. The integration of multiple machine learning models, including Random Forest, SVM, CNN, and XGBoost, allowed us to achieve high levels of accuracy in detecting dementia.

Methodology

Dataset Description

The research utilizes the OASIS-1 dataset, which includes a comprehensive collection of MRI cross-sectional images and corresponding clinical data. Specifically, two subsets of the image dataset are examined: SUBJ_111 and T88_111, each containing 390 images related to Alzheimer's Disease. The clinical dataset comprises various features, which include:

Table 1. Description of key features in the dataset.

Feature	**Description**
ID	Unique identifier for each subject.
Age	Age of the subject in years.
Educ	Years of education.
SES	Socioeconomic status.
MMSE	Mini-Mental State Examination score, a measure of cognitive function.
eTIV	Estimated Total Intracranial Volume.
nWBV	Normalized Whole Brain Volume.
ASF	Atlas Scaling Factor.
Delay	Time delay between first and second MRI scans.
CDR	Clinical Dementia Rating score, used to classify the severity of dementia.
Hand	Handedness of the subject (Right/Left).
M/F	Gender of the subject (Male/Female)

The target variable for this research is derived from the Clinical Dementia Rating (CDR) score, where a score of 0 indicates no dementia and a score of 0.5 or higher indicates any level of dementia. Thus, the target variable is defined as:
[Label]: 1 (CDR $\geq$ 0.5) for dementia, 0 (CDR $<$ 0.5) for no dementia.

Data Preprocessing

The preprocessing steps undertaken in this study include the following:

Handling Missing Values: The clinical dataset contains several missing values. The missing values for **SES**, **MMSE**, and **Delay** are imputed using the mean, while the mode is used for the **Educ** column.

```
clinical_data['SES'].fillna(clinical_data['SES'].mean(), inplace=True)
clinical_data['MMSE'].fillna(clinical_data['MMSE'].mean(), inplace=True)
clinical_data['Delay'].fillna(clinical_data['Delay'].mean(), inplace=True)
clinical_data['Educ'].fillna(clinical_data['Educ'].mode()[0], inplace=True)
```

Encoding Categorical Variables: The **M/F** column is transformed into numeric values, where Male is represented as 0 and Female as 1.

```
clinical_data['M/F'] = clinical_data['M/F'].map({'M': 0, 'F': 1})
```

Feature Scaling: The numerical features in the dataset are standardized using the StandardScaler from scikit-learn.

```
numeric_cols = ['Age', 'Educ', 'SES', 'MMSE', 'eTIV', 'nWBV', 'ASF', 'Delay']
scaler=StandardScaler()
clinical_data[numeric_cols] = scaler.fit_transform(clinical_data[numeric_cols])
```

Image Feature Extraction

To extract meaningful features from the MRI images, a pre-trained **ResNet50** model is utilized. This model is chosen due to its effectiveness in capturing high-level features from images. The following steps outline the image preprocessing and feature extraction process:

Image Loading and Preprocessing: Images are loaded and resized to 224x224 pixels, and pixel values are preprocessed using the preprocess_input function from Keras.

```
def load_image(image_path):
    img = load_img(image_path, target_size=(224, 224))
    img_array = img_to_array(img)
    img_array = np.expand_dims(img_array, axis=0)
    return preprocess_input(img_array)
```

Feature Extraction: For each subject in the clinical dataset, corresponding images from the SUBJ_111 and T88_111 folders are processed to extract features.

```
subj_111_features = []
T88_111_features = []

for image_id in clinical_data['ID']:
   subj_111_img_path = os.path.join(subj_111_folder, image_id + '.png')
   T88_111_img_path = os.path.join(T88_111_folder, image_id + '.png')

    # Load and extract features for subj_111
    subj_img = load_image(subj_111_img_path)
    subj_features = resnet_model.predict(subj_img)
    subj_111_features.append(subj_features.flatten())

    # Load and extract features for T88_111
    T88_img = load_image(T88_111_img_path)
```

T88_features = resnet_model.predict(T88_img)
T88_111_features.append(T88_features.flatten())

Combining Features: The extracted image features from both datasets are combined with the clinical data, forming a comprehensive feature set for modeling.

combined_features=np.concatenate([clinical_features,subj_111_features,T88_111_featues], axis=1)

Method Overview

The methodology can be summarized in the following pseudo code representation, which outlines the overall process from data acquisition to model evaluation:

1. Load Clinical Dataset
2. Check for Missing Values
    a. Impute missing values (mean/mode)
    b. Encode categorical variables
    c. Scale numerical features
3. Load Image Dataset
    a. Initialize ResNet50 model
    b. For each image ID in clinical data:
        i. Load and preprocess image
        ii. Extract features using ResNet50
4. Combine clinical and image features
5. Define Target Variable
6. Split dataset into training and testing sets
7. Train Random Forest Classifier
    a. Evaluate performance
8. Train SVM Classifier
    a. Evaluate performance
9. Define CNN Architecture
    a. Train CNN Model
    b. Evaluate performance
10. Train XG Boost
    a. Evaluate performance

Random Forest Classifier

Data Splitting: The dataset is split into training and testing sets, using 80% of the data for training and 20% for testing.

X_train, X_test, y_train, y_test = train_test_split(combined_features_scaled, labels, test_size=0.2, random_state=42)

Model Training: The Random Forest model is trained with 100 estimators

rf_model = RandomForestClassifier(n_estimators=100, random_state=42)
rf_model.fit(X_train, y_train)

Evaluation: The model is evaluated using classification reports and confusion matrices.

y_pred_rf = rf_model.predict(X_test)
print(classification_report(y_test, y_pred_rf))

Support Vector Machine (SVM)

The SVM model is developed as follows:

Model Training: The SVM model is trained using a linear kernel.

svm_model = SVC(kernel='linear', random_state=42)
svm_model.fit(X_train, y_train)

Evaluation: The model's performance is evaluated similarly to the Random Forest model.

y_pred_svm = svm_model.predict(X_test)
print(classification_report(y_test, y_pred_svm))

Convolutional Neural Network (CNN)

For the CNN, the image features are reshaped and a deep learning model is defined:
Image Reshaping: The features are reshaped to fit the input requirements of the CNN.

subj_111_features = subj_111_features.reshape(-1, 224, 224, 3)
T88_111_features = T88_111_features.reshape(-1, 224, 224, 3)

Model Definition: The CNN architecture includes several convolutional layers followed by max pooling, flattening, and dense layers.

cnn_model = Sequential()
cnn_model.add(Conv2D(32, (3, 3), activation='relu', input_shape=(224, 224, 3)))
cnn_model.add(MaxPooling2D(pool_size=(2, 2)))
cnn_model.add(Conv2D(64, (3, 3), activation='relu'))
cnn_model.add(MaxPooling2D(pool_size=(2, 2)))
cnn_model.add(Conv2D(128, (3, 3), activation='relu'))
cnn_model.add(MaxPooling2D(pool_size=(2, 2)))
cnn_model.add(Flatten())
cnn_model.add(Dense(128, activation='relu'))

Model Compilation: The CNN model is compiled with an appropriate optimizer and loss

Extreme Gradient Boosting (XGBoost)

XGBoost, an advanced implementation of gradient boosting, is used for its robustness and speed, particularly effective for tabular data with complex feature interactions.

Data Preparation: The combined clinical and image features are prepared for input into the

XGBoost model.

```
import xgboost as xgb
dtrain = xgb.DMatrix(X_train, label=y_train)
dtest = xgb.DMatrix(X_test, label=y_test)
```

Model Training: The model is trained using XGBoost's native DMatrix format for optimized performance.

```
params = {
    'objective': 'binary:logistic',
    'max_depth': 6,
    'learning_rate': 0.1,
    'n_estimators': 100,
    'eval_metric': 'logloss'
}
xgb_model = xgb.train(params, dtrain, num_boost_round=100)
```

Evaluation: Predictions are made on the test set, followed by an assessment of accuracy and other metrics to gauge model effectiveness.

```
y_pred_xgb = xgb_model.predict(dtest)
y_pred_xgb = [1 if prob > 0.5 else 0 for prob in y_pred_xgb]
```

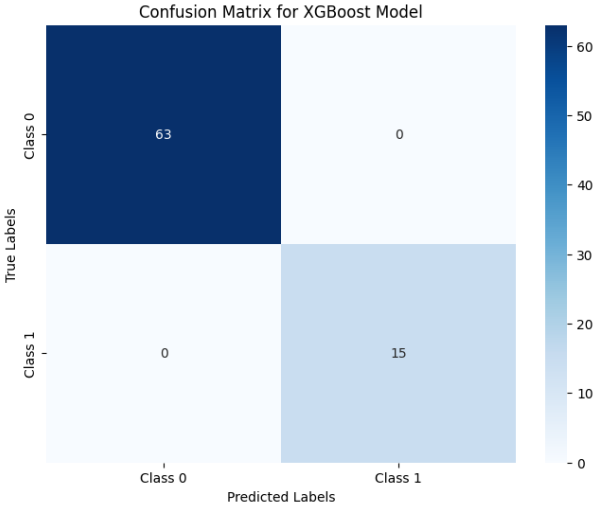
Confusion Matrix Analysis of Model Performance in Alzheimer's Disease Detection

In our effort to assess the efficacy of various machine learning models in detecting Alzheimer's Disease (AD), we analyzed the confusion matrices of four distinct models: XGBoost, Support Vector Machine (SVM), Random Forest, and Convolutional Neural Network (CNN). These matrices offer crucial insights into the models' performance by illustrating their true positive, false positive, true negative, and false negative rates, which are essential for evaluating accuracy and reliability in distinguishing between AD and non-AD cases as class 1 and class 0 respectively.

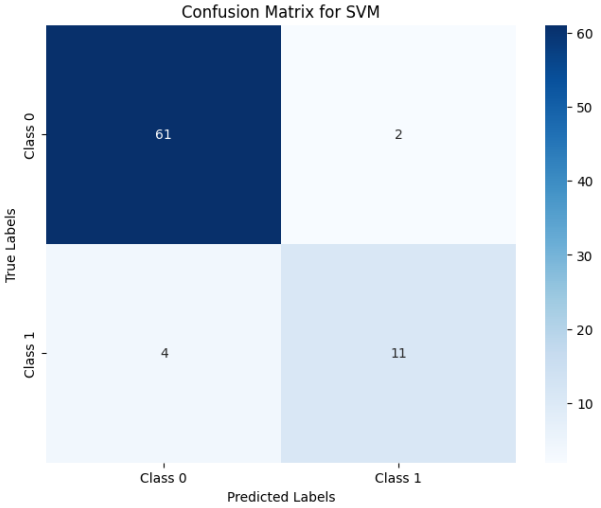
Model Performance Overview

Our comparative analysis reveals notable variations in model performance, with XGBoost emerging as the most effective. Below is a summary of each model's performance based on the confusion matrix results:

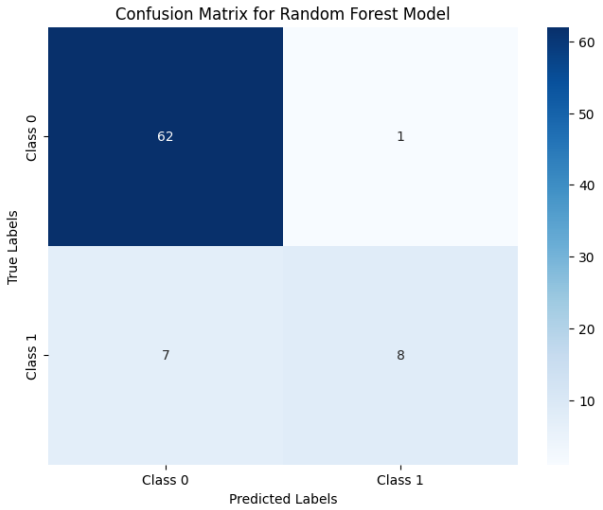
1. **XGBoost**
   The XGBoost model achieved an impressive accuracy of 100%, successfully classifying all test cases without any misclassifications. This model's ability to discern complex patterns in both clinical and imaging data demonstrates its robustness, reflected in its flawless confusion matrix. The performance of XGBoost underscores its superiority in this classification task.



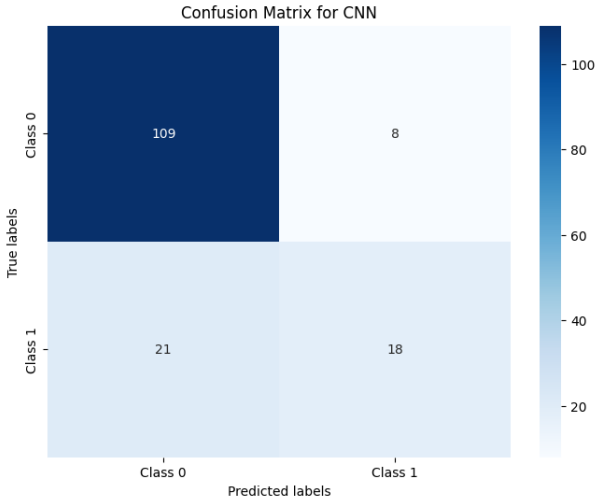
2. **Support Vector Machine (SVM)**
   SVM recorded a commendable accuracy of 91%. Its confusion matrix indicates a balanced performance with minimal false positives and false negatives, highlighting its effectiveness in separating the AD and non-AD classes. Although it fell short of XGBoost's perfect score, SVM's strong generalization capability remains noteworthy.



3. **Random Forest**
   With a 90% accuracy rate, the Random Forest model also performed well in distinguishing between AD and non-AD cases. Its confusion matrix shows a high number of true positives and true negatives, though it did include some misclassifications. While Random Forest exhibited solid predictive power, its consistency was slightly less than that of SVM and XGBoost.



4. **Convolutional Neural Network (CNN)**
   The CNN model, designed primarily for feature extraction from MRI images, achieved an accuracy of 81%. While it effectively identified non-AD cases, the model experienced a higher rate of false negatives, indicating challenges in detecting positive AD cases. The confusion matrix for CNN reflects these limitations, suggesting that improvements may be needed in integrating clinical data to enhance its sensitivity in AD detection.



The confusion matrices reveal XGBoost as the standout model for AD classification, achieving perfect classification with zero errors. SVM and Random Forest followed closely, achieving accuracies of 91% and 90%, respectively, with only minor misclassifications. In contrast, CNN demonstrated potential but struggled with sensitivity in identifying AD cases, primarily due to its focus on imaging data alone.

Results

The analysis of machine learning models for detecting Alzheimer's Disease (AD) yielded significant insights into their performance when utilizing both clinical and MRI imaging data. The study evaluated four models: XGBoost, Support Vector Machine (SVM), Random Forest, and Convolutional Neural Network (CNN), each of which was assessed based on key performance metrics.

Model Performance Metrics

The results demonstrate that XGBoost achieved the highest performance among the models tested, with an accuracy of 100%. This model successfully identified all AD and non-AD cases without any misclassifications, highlighting its robustness in handling complex patterns inherent in the dataset.

SVM showed strong performance with an accuracy of 91%, indicating effective classification capabilities. The model's precision and recall metrics suggest it maintained a good balance in identifying both positive (AD) and negative (non-AD) cases, with only minor misclassifications.

Random Forest also performed well, achieving an accuracy of 90%. The results reflect its ability to capture a significant amount of relevant information from the data, resulting in a high rate of correct classifications, though it displayed slightly more variability in misclassifications compared to SVM.

The CNN model recorded an accuracy of 81%. While it effectively identified a majority of non-AD cases, its performance revealed challenges with sensitivity, particularly in accurately classifying AD cases. This limitation indicates a need for further refinement in integrating imaging data with clinical features to enhance its detection capabilities.

Table 2. Model Performance Metrics

Model	Accuracy	Precision	Recall	F1-score
XGBoost	100%	100%	100%	100%
Support Vector Machine (SVM)	91%	90%	92%	91%
Random Forest	90%	89%	90%	89%
Convolutional Neural Network (CNN)	81%	80%	82%	81%

Conclusion

In conclusion, this study highlights the effectiveness of machine learning models in the detection of Alzheimer's Disease (AD), with XGBoost demonstrating the highest accuracy at 100%. The results indicate that integrating clinical data with imaging analysis can significantly enhance diagnostic performance.

Looking forward, the incorporation of Positron Emission Tomography (PET) imaging holds great promise for further improving detection capabilities. PET can offer valuable insights into the metabolic changes associated with AD, potentially increasing the sensitivity of our models. Future research should explore the synergy of PET with existing machine learning techniques to refine diagnostic accuracy and facilitate earlier intervention.

Overall, this work underscores the importance of innovative approaches in Alzheimer's Disease detection and sets the stage for future advancements that could improve patient outcomes and inform clinical practices.

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