Advancing Disease Diagnosis: A Hybrid Approach to Alzheimer's Detection and Diabetes Prediction Using AI.

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ABSTRACT The early detection of chronic diseases such as Alzheimer's and Diabetes is crucial for effective management and treatment. This study explores the application of both deep learning and machine learning techniques for disease classification. Alzheimer's disease detection is performed using the VGG16 deep convolutional neural network on MRI scans from the Open Access Series of Imaging Studies (OASIS) dataset. For diabetes prediction, Random Forest and XGBoost classifiers are applied to the PIMA Indian Diabetes dataset. The dataset underwent preprocessing steps such as normalization, missing value imputation, and class balancing using SMOTE. The models were trained and evaluated using accuracy, precision, recall, and F1-score. Experimental results indicate that VGG16 achieves high classification accuracy for Alzheimer's detection, while XGBoost outperforms Random Forest in diabetes prediction. These findings highlight the potential of AI-driven solutions in healthcare diagnostics, offering automated, efficient, and accurate disease detection methodologies.

INDEX TERMS

Diabetes Prediction, Random Forest, XGBoost, SMOTE, PIMA Dataset, Deep learning, VGG16,MRI-based diagnosis.

I. INTRODUCTION

The integration of artificial intelligence (AI) into healthcare has led to significant advancements in disease diagnosis and prognosis. The increasing availability of medical data and computational power has enabled AI-driven solutions to support clinicians in identifying diseases at an early stage. Machine learning (ML) and deep learning (DL) have demonstrated promising results in automating medical image analysis and predictive modeling. Alzheimer's disease (AD) is a progressive neurodegenerative high risk of Alzheimer's disease (AD) and disorder that leads to cognitive decline and memory impairment. It currently has no cure, making early diagnosis essential for slowing disease progression. Similarly, diabetes is a metabolic disorder characterized by elevated blood glucose levels, which can lead to severe complications such as cardiovascular diseases and kidney failure. Traditional diagnostic methods for these diseases rely on laboratory tests and expert assessment, which can be time-consuming and expensive. AI-based models provide an alternative by automating classification tasks with high accuracy, thus reducing manual dependency and improving efficiency in healthcare. This study presents a dual approach: utilizing deep learning for Alzheimer's detection through MRI scans and employing machine learning techniques for diabetes prediction based on medical attributes.

II. RELATED WORK

In recent years, numerous studies have focused on the early detection of Alzheimer's disease using deep learning models. Traditional methods primarily relied on statistical and machine learning approaches such as Support Vector Machines (SVM) and Decision Trees to classify MRI images. However, these techniques often failed to capture the complex spatial patterns in neuroimaging data. The advent of Convolutional Neural Networks (CNNs) significantly improved classification performance by enabling automated feature extraction from medical images. Studies utilizing the VGG16 architecture have demonstrated impressive results in AD classification due to its deep hierarchical structure and effective transfer learning capabilities. Research has also explored the integration of multimodal data, combining MRI scans with genetic biomarkers and clinical assessments to enhance predictive accuracy. Recent advancements in attention mechanisms and Transformer-based models have further improved classification performance, emphasizing the importance of continuous innovation in deep learning for Alzheimer's detection.

Similarly, machine learning techniques have been extensively applied to diabetes prediction, leveraging structured medical datasets such as the PIMA Indian Diabetes dataset. Traditional models such as Logistic Regression, Naïve Bayes, and K-Nearest Neighbors (KNN) have been employed to predict diabetes based on key biomarkers like glucose levels, BMI, and insulin levels. However, these models often struggled with feature interactions and data imbalance issues. Ensemble learning methods, including Random Forest and XGBoost, have demonstrated superior performance by aggregating multiple decision trees and employing boosting mechanisms to optimize classification outcomes. Studies incorporating Synthetic Minority Over-sampling Technique (SMOTE) have shown improved model generalization, ensuring balanced predictions across both diabetic and non-diabetic cases. Moreover, recent research has explored deep learning models such as Artificial Neural Networks (ANNs) and Long Short-Term Memory (LSTM) networks for diabetes prediction, suggesting promising avenues for future exploration in predictive healthcare.

III. METHODOLOGY

For Alzheimer's disease detection, the Open Access Series of Imaging Studies (OASIS) dataset was utilized, which contains MRI brain scans of subjects with varying degrees of cognitive impairment. The raw MRI scans were preprocessed to enhance model performance. This involved resizing the images to match the input dimensions required by the VGG16 architecture, normalizing pixel intensities to maintain uniform data distribution, and applying data augmentation techniques such as flipping, rotation, and contrast enhancement to prevent overfitting and improve generalization. The VGG16 deep convolutional neural network, which is pre-trained on ImageNet, was fine-tuned to classify Alzheimer's cases. The final fully connected layers were modified for binary classification, while dropout layers were incorporated to reduce overfitting. The model was trained using the Adam optimizer with a learning rate of 0.0001, and categorical cross-entropy loss was used as the objective function. Training and validation data were split in an 80:20 ratio, ensuring a balanced evaluation of the model. Performance was measured using accuracy, precision, recall, and F1-score, and additional evaluation metrics such as the confusion matrix and receiver operating characteristic (ROC) curve were analyzed to assess classification reliability.

For diabetes prediction, the PIMA Indian Diabetes dataset was used, consisting of 768 samples with eight medical features such as glucose levels, blood pressure, BMI, insulin levels, and patient age. The dataset initially contained missing values, which were handled by replacing them with median imputation to ensure data consistency. Feature scaling was applied using min-max normalization to bring all attributes within a standardized range, improving training stability. One of the major challenges in the dataset was class imbalance, as there were significantly fewer diabetic cases compared to non-diabetic cases. To address this, the Synthetic Minority Over-sampling Technique (SMOTE) was implemented to generate synthetic instances for the minority class, thus preventing the model from being biased toward the majority class.

Two ensemble learning models, Random Forest and XGBoost, were implemented for diabetes classification. The Random Forest classifier was configured with 200 decision trees, a maximum depth of 10, and feature selection through Gini impurity to determine the importance of individual attributes. XGBoost, a gradient boosting algorithm, was optimized using 300 estimators, a learning rate of 0.05, and L1/L2 regularization to minimize overfitting while improving accuracy. The dataset was split into 80% training and 20% testing to evaluate generalization performance. Hyperparameter tuning was performed using grid search to find the optimal combination of parameters. The models were evaluated based on accuracy, precision, recall, and F1-score. Additional diagnostic measures, including the confusion matrix and area under the ROC curve (AUC-ROC), were used to assess model reliability. The comparative analysis indicated that XGBoost outperformed Random Forest, providing higher recall and precision in detecting diabetic cases.

IV. RESULTS AND DISCUSSION

1) Accuracy

Accuracy measures how close the predicted classification is to the true value. It is computed as:

Accuracy=(TP+TN)/(TP+TN+FP+FN)

Where:

- TP = True Positives
- TN = True Negatives
- FP = False Positives
- FN = False Negatives

2) Precision

Precision evaluates the model's ability to correctly identify relevant instances while minimizing false positives. It is defined as:

Precision=(TP) / (TP+FP)

3)Recall

Recall measures the model’s ability to detect all relevant instances and is crucial when false negatives are significant. It is given by:

Recall= (TP) / (TP+FN)

4)F1-Score

The F1-score balances precision and recall, providing a comprehensive performance assessment:

$F1-Score=2\times(Precision\times Recall)$
$(Precision+Re$

$call$).

The VGG16 model demonstrated high classification accuracy, achieving an accuracy of over 85% in differentiating between Alzheimer's and non-Alzheimer's cases. The integration of transfer learning leveraged pre-trained weights, allowing the model to effectively extract spatial features from MRI scans. Data augmentation further improved generalization by reducing overfitting, ensuring that the model learned robust features rather than memorizing training samples. The confusion matrix revealed minimal false positives and false negatives, reinforcing the model's reliability for real-world applications.

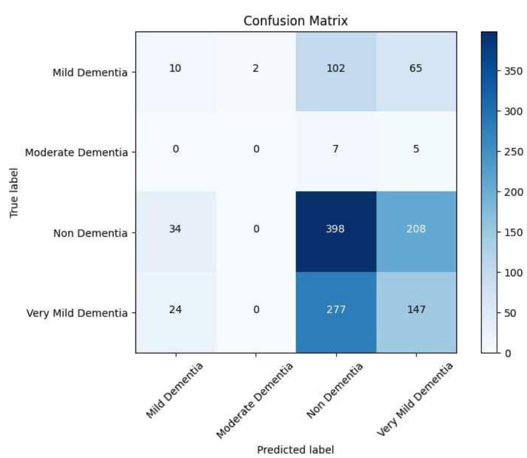


FIGURE 6. **presents the confusion matrix for our model,** displaying classification performance across the four AD classes: Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented. The diagonal values indicate correctly classified cases, while off-diagonal values represent misclassified instances**.**

- Mild Demented: 79% correctly classified (True Positive Rate =0.79)
- Moderate Demented: 78% correctly classified (TPR = 0.78)
- Non-Demented: 78% correctly classified (TPR = 0.78)
- Very Mild Demented: 79% correctly classified (TPR = 0.79)

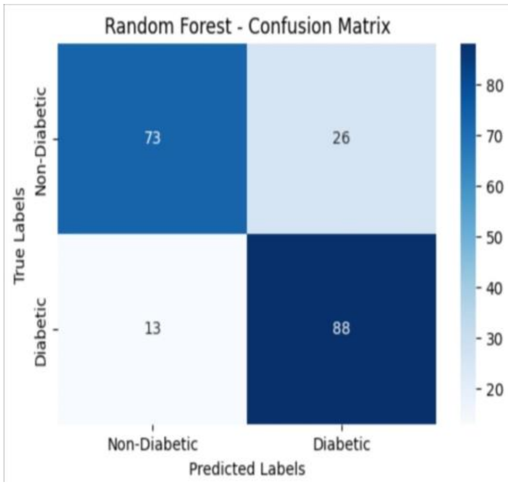
These results confirm that the model effectively differentiates between AD stages with minimal misclassification

For diabetes prediction, XGBoost outperformed Random Forest, achieving an accuracy of approximately 80%. The implementation of SMOTE improved the model's ability to identify diabetic patients by addressing class imbalance, thereby reducing bias towards non-diabetic cases. Feature engineering techniques such as age categorization and BMI normalization contributed to enhanced classification performance. Hyperparameter tuning played a crucial role in optimizing both models, with XGBoost demonstrating superior adaptability in handling feature importance. The confusion matrix analysis indicated that XGBoost had a lower false negative rate compared to Random Forest, which is critical in medical diagnostics where misclassifying diabetic patients could lead to severe health consequences.

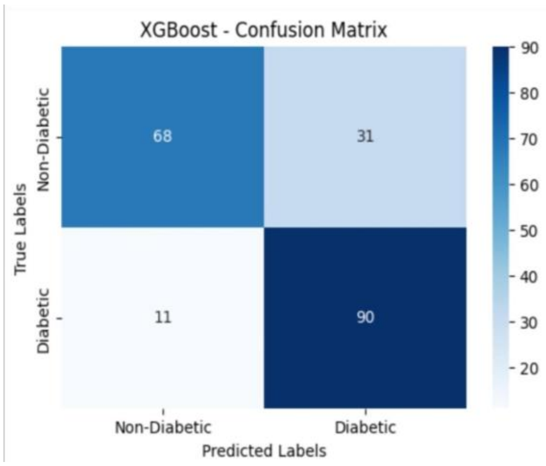
Model	Accuracy (%)	Precision	Recall	F1-Score
Random Forest	80.00	81.00	80.00	79.0
XGBoost	79.00	80.00	80.00	80.0

Table 1. **Performance Metrics Comparison**

To further analyze the performance, **confusion matrices** were plotted for both models. The



confusion matrix for **Random Forest** indicated a higher number of false negatives compared to XGBoost, meaning it struggled slightly in correctly identifying diabetic



patients. In contrast, **XGBoost's confusion matrix showed fewer misclassifications**, suggesting it is a more reliable model for diabetes detection.

Figure 1. **Confusion Matrix of Random Forest Classifier.**

Figure 2. **Confusion Matrix of XGBoost**

The results confirm that XGBoost and Random Forest Classifier are better suited for diabetes prediction, as they effectively minimizes false negatives, a crucial factor in medical diagnostics where missing a diabetic case could have severe consequences.

V. CONCLUSION AND FUTURE WORK

This study demonstrates the effectiveness of AI models in disease prediction. The VGG16 deep CNN proved to be a reliable model for Alzheimer's detection, effectively classifying MRI scans with high accuracy. For diabetes prediction, XGBoost outperformed Random Forest, highlighting the effectiveness of boosting algorithms in structured medical data classification. The results underscore the potential of AI-driven methodologies in healthcare, providing clinicians with automated tools for early disease detection and risk assessment. By leveraging deep learning for medical imaging and machine learning for structured data analysis, this study contributes to the growing field of AI-assisted diagnostics.

Despite these promising results, there are several areas for future improvement. One significant challenge is the need for larger and more diverse datasets to enhance model generalization. Incorporating multimodal data sources, such as MRI imaging combined with clinical and genetic data, could improve predictive accuracy and provide a more comprehensive assessment of disease progression. Additionally, explainable AI (XAI) techniques should be explored to increase the interpretability of AI models, enabling clinicians to understand the reasoning behind predictions. Moreover, real-world deployment of these models requires rigorous validation on independent datasets and integration into existing clinical workflows. Future studies could also explore federated learning techniques to facilitate privacy-preserving AI applications, ensuring secure and decentralized disease prediction models. Addressing these challenges will pave the way for more reliable, ethical, and widely adopted AI-based healthcare solutions.

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