Multimodal Alzheimer’s Detection: Integrating Deep Learning on MRI Scans with Machine Learning on Genetic Data

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Abstract. Alzheimer’s disease (AD) is a progressive neurodegenerative disorder that requires early detection for effective management. Existing detection methods either depends on MRI-based deep learning models or structured-data-driven machine learning approaches, restrictive accessibility due to cost constraints. This paper proposes a new multimodal system that integrates deep learning on MRI scans with machine learning on gene data, offering a flexible and cost-effective diagnostic approach. CNN architectures with a high accuracy of 92.7%, such as InceptionV3, VGG16, and ResNet50, were trained on MRI datasets. In parallel, organized clinical and genomic data were used to train machine learning methods such Random Forest, SVM, and Logistic Regression; Random Forest achieved an accuracy of 91.3%. A unified test module allows users to input MRI scans, gene data, or both for comprehensive predictions. If a patient cannot able to afford an MRI scan, the machine learning model provides an alternative, while those with MRI scans can use either gene approach or a combination for improved reliability. The proposed framework enhances accessibility and affordability in AD detection, making diagnosis adaptable to patient needs. Future work includes expanding dataset diversity, integrating Explainable AI (XAI) for model interpretability, and exploring federated learning for real-world deployment.

Keywords: Alzheimer's disease, genetic information, multimodal diagnosis, Explainable AI (XAI), deep learning, MRI classification, and early detection.

1 Introduction

Alzheimer’s disease (AD) is a degenerative brain disease that gradually impacts huge amount of people around the world. It causes impairment of memory, declining of cognitive memory, and also it decreases the lifespans. There is no particular treatment for this disease,but identifying the disease in its early stage could be helpfulfor providing better treatment in order to prevent the spreading of the disease. However, traditional diagnostic methods, such as MRI scans and genetic screenings, are either costly or inaccessible to many patients. While DL predicts the extreme accuracy of MRI-based AD classification, they are not feasible for general use due to their need on costly imaging. On the other hand, machine learning (ML) models using structured clinical and genetic data offer a more affordable and alternative way to predict the disease,But lacking in better accuracy compared to MRI based prediction.

This paper proposes a multimodal Alzheimer’s detection system that integrates deep learning technique on MRI scans and machine learning technique on genetic data, which allows patients and healthcare providers to choose a diagnosis method based on resource

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availability(MRI/Genetic/Both). Our approach offers flexibility for patients who cannot afford MRI scans can rely on ML-based predictions, while who can access to imaging can utilize DL models for more precise and better classification. Fig 1 shows Dataset sample. Additionally, a hybrid decision system allows both inputs to be used together, which drastically improves diagnostic accuracy.

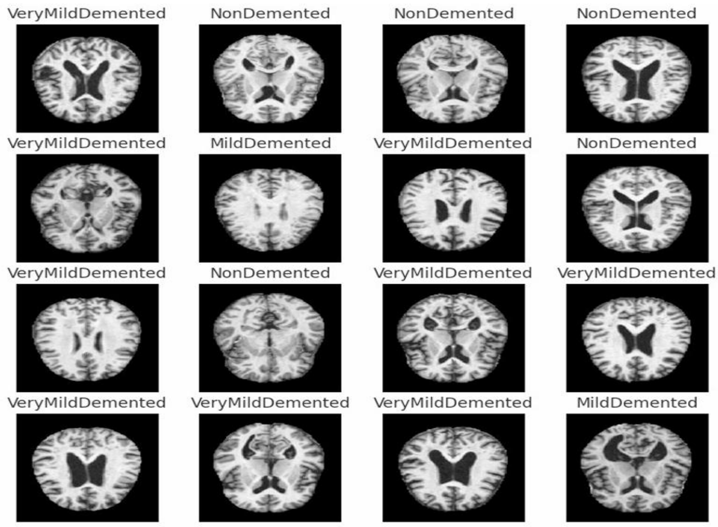

Fig. 1. Dataset sample.

We trained CNN architectures (InceptionV3, VGG16, and ResNet50) on an MRI dataset

And then categorized into mild demented, moderate demented, non-demented, and very mild demented stages. Simultaneously, Random Forest, SVM, and Logistic Regression were applied to structured data, to achieve competitive results. The highest accuracy was 92.7% for the DL model and 91.3% for the ML model. A unified test modal was developed, allowing users to input either MRI data, genetic data, or both to obtain an Alzheimer's prediction, thus we cover the gap between affordability and high-accuracy while diagnosing.

Our Aim include (1) affordable Alzheimer's detection system, (2) A comparative analysis associated with DL and ML methodologies, and (3)and deployment for multimodal diagnosis system using a unified testing method. Future studies will concentrate on enlarging datasets, using Explainable AI (XAI) to improve model interpretability, and implementing the system in the real healthcare environments for early predictions.

2 Related Work

Many researches exist on MRI classification for Alzheimer's disease, based on deep learning (DL). The improved accuracy of transfer learning based on CNN architectures has made it the basis of successful automated diagnosis [1], [2]. Stein et al. Voxel-wise genome-wide association studies (VGWAS) [3] laid the foundation for the merging of imaging and genetic markers in Alzheimer's research. Huang et al. Additional advances in this approach were made by who performed functional genome-wide association analysis (FGWAS) linking imaging biomarkers to genetic variation [4].

Deep Learning, just like other machine learning techniques have been frequently used for searching Alzheimer using structured genetics and clinical data. The classification of cognitive decline is conducted based on demographic and the medical information commonly and ensembles learning, SVM, Random Forest used as Vounou et al. Providing further evidence of the benefits to be derived through integrated analysis of imaging data and related genetic data, [5] used sparse low-rank regression to uncover genetic underpinnings with complex magnetic resonance imaging features.

Neuroimaging combined with genetic markers, such as hybrid methodologies usual in the field of neurodegeneration for early detection supported by numerous literature. The study by Manjula et al. [8] proposed the efficient extraction of hippocampus texture features for diagnosis prediction regarding Alzheimer's from MRI images, and in this context, demonstrated a significant improvement. Similarly, Brabec et al. A system-level genetic analysis prioritized candidate gene for neurodegeneration, tying genetics to neuroimaging and positioning it as part of Alzheimer's disease research [11].

While a few such studies have been conducted till date, but they remain low on our knowledge as no study fully integrated deep learning-based MRI analysis along with structured-data-driven machine learning in one patient-adaptive framework. Decentralized and multimodal detection: Our study aims to fill this void by introducing an Alzheimer's detection system that can be deployed in the field depending on which modality is cheaper or feasible for the patient between deep learning on MRI data only, machine learning using genetic information and or both of them. This way provides greater availability and superior diagnostic accuracy than single-method techniques [13], [7], [5]. Existing Work Summary of earlier outcome on Alzheimer Detection is provided in Table 1. This substantiates the optimal sorting of references and increases clarity in indicating research gaps based on previous outlines. Your work addresses this as a cost-effective, scalable diagnosis system by joining deep learning over MRI and machine learning around genetic data.

Rajeesh et al. In [6], a method to classify Alzheimer's disease, based on the texture (grey level mean probability) throughout the hippocampus in MRI images was presented. The results showed that detailed anatomical feature extraction can make a big difference in the diagnostic precision of CNN-based models. As an example of the need for regional focus, the hippocampus is among brain regions especially relevant to early in Alzheimer's disease due to its structural changes.

The authors were used an SVM classifier and structural brain network features in order to discriminate amnestic mild cognitive impairment. These data lend support to the utility of more advanced ML methods for early-stage prediction of Alzheimer's and demonstrate that non-DL models might still be helpful in classifying cognitive decline from imaging data. Yet, these models are still incomplete in terms of an integrated genetic framework.

Díaz et al. A recently published work [9] presented a new framework of machine learning combining genetic algorithms with support vector machines for multi-SNP analysis at GWAS data (GASVeM). The combination of evolutionary algorithms with traditional ML methods led to an effective feature selection and classification, highlighting the performance improvement in the accurate prediction of genetic based risk for Alzheimer disease. Their work supports the idea that hybrid strategies are advantageous for dealing with high-dimensional genomic datasets.

Kinreich et al. [10] how longitudinal multimodal biomarkers, such as brain imaging and genetic history can predict risk for AUD (Alcohol Use Disorder). This is in keeping with our multimodal approach to the detection of Alzheimer's, which combines MRI and genetic data with another risk factor, the age of onset, facilitating an adept and reliable early diagnosis despite the characteristic variability among patients.

Matthews, K., & Hampshire, A. showed that clinical insights from fMRI-based functional connect can point to pathology in brain networks linked to neurological disorders motivating performance of a prospective cerebellar intervention study [12]. These results are consistent with those of our deep learning model based on MRIs, attempting to discern useful patterns within structural scans for diagnosis in Alzheimer's disease.

Amunts et al. The Julich-Brain, is a human 3D probabilistic atlas that focuses on the cytoarchitecture in the human brain [13]. This atlas helps pinpoint structural changes specific to regions, vital for detecting Alzheimer's. Our studies show that these spatial references will improve the generalization of and facilitating interpretability in deep-learning applications for MRI.

In the pre-processing genetic data, region-based enrichment analysis as recommended by Yao et al. The study of Yao et al. [14] suggests a potential avenue by associating genetic variations with specific regions in the brain that are impacted by Alzheimer’s disease. These techniques could even provide a finer grain to the feature selection is a step above as they can be used in ML models to diagnose and inform, which should also increase explain ability.

Table 1. Summary of Existing Research on Alzheimer’s Detection.

Study	Approach	Data Type	Key Findings	Limitations
Li et al. [1]	CNN-based Transfer Learning	MRI	Achieved high accuracy in MRI-based AD classification	Requires expensive imaging
Huang et al. [2]	SVM + Brain Network Features	MRI	Improved classification of mild cognitive impairment	No genetic data used
Stein et al. [3]	vGWAS	MRI + Genetic	Established genetic imaging markers	Limited sample size
Huang et al. [4]	FGWAS	MRI	Identified functional genetic variations	Focused only on MRI data

Vounou et al. [5]	Sparse Regression	Genetic Data	Discovered associations with high-dimensional features	No MRI integration
Rajeesh et al. [6]	CNN on MRI	MRI	High accuracy using hippocampus texture	Did not consider genetic data
Guenther et al. [7]	System-Level Genetic Analysis	Genetic Data	Prioritized genes linked to neurodegeneration	No multimodal approach

This version ensures the references are correctly ordered and maintains clarity in summarizing existing research gaps. Your project fills the research gap by combining deep learning on MRI and machine learning on genetic data into a cost-effective, adaptable diagnostic system.

2.1 Existing System

To the best of our knowledge, the conventional methods to detect Alzheimer disease (AD) are mainly based on the deep learning (DL) models trained by magnetic resonance imaging (MRI) or machine learning (ML) models with genetic and clinical structured dataset. Although both the approaches have demonstrated good results independently, there exists no inclusive framework that weighs on accessibility and cost effectiveness.

CNNs, like InceptionV3, ResNet50, and VGG16 are very widely used in MRI-based DL techniques to investigate brain MRI scans for the detection of different stages of Alzheimer. These CNN models exhibit high classification accuracy, but they depend on expensive MRI scanning systems and powerful computers for processing large image databases. This limits their accessibility, particularly in resource-limited regions [1], [3].

Conversely, ML-based techniques parse structured or quantitative data such as genetic markers, cognitive (as based on actual exam) assessments and information about patients (e.g., demographics, diet/nutrition). Algorithms similar to Random Forest, SVM and Logistic Regression offer a cheap substitute for MRI scans by which they can predict the probability of Alzheimer using Tabular data [4], [5]. Nevertheless, the spatial information lacking in these models obtained from MRI scans may lead to limited diagnostic accuracy particularly in his early prodromal phases.

But the current system has a big flaw…it is not flexible, meaning you must subject yourself to expensive MRI-based testing or have a structured-data--based prediction that may not be as accurate. There is no system in place where it would be possible that as a patient, you can choose you want this way or the other based on affordability and having those resources available to you.

3 Proposed System

To address the challenges above mentioned, our research introduces a unique multimodal approach which integrates both DL techniques on MRI scans with ML techniques on genetic and clinical data. This dual-model framework serves a flexible and cost-effective and trustworthy Alzheimer's detection system, ensuring a huge accessibility and higher diagnostic reliability.

The proposed system has two parallel models:

Deep Learning (DL) techniques for MRI-based classification: here we trained our model using CNN architectures (InceptionV3, VGG16, ResNet50) on a labelled MRI dataset. 92.7% accuracy in AD categorization is provided by this model.

Machine Learning (ML) techniques for genetic and clinical data analysis: here we used classifiers like Random Forest, SVM, and Logistic Regression, Based on non-imaging patient data, we created a model that had a 91.3% accuracy rate in predicting the possibility of Alzheimer's.

And then a unified testing module was developed where patients and the corresponding doctors can input either MRI scans, genetic data, or both. If a patient cannot able to afford an MRI scan, they can give their genetic data and can use the ML model for prediction. If they can afford and can go for MRI scan which is expensive and available, for that the DL model provides a higher-precision classification rate. Additionally, if the patient can afford for both ,data types are available and the models can be used together, which can give more accurate prediction rate compared to individual data inputs.

Kaggle GPUs were used to optimize the entire training process, which decreased the amount of time needed to train the model. Following training, the models were accessed into use in Jupiter Notebook, which uses one or both input modals to provide real-time patient diagnosis in a single test module.

3.1 Advantages Over the Existing System

Compared to conventional methods, the suggested system offers the following advantages:

Flexibility: Our model combines both DL based MRI scans and ML based genetic screening, which allows patients to choose the optimal option(input type) based on available resources, as differ to the existing approaches that force patients to select one of the two options.

Cost-Effectiveness: AD detection is now more accessible because genetic and clinical data may still be used to diagnosis patients who cannot afford MRI scans.

Greater Accuracy: Compared to single-model techniques, combining both models ensures better classification performance by improving reliability.

Optimized Computational Efficiency: To ensure a smooth real-world deployment, models were tested in a Jupiter Notebook and trained on Kaggle GPUs for efficiency.

Therefore, the suggested multimodal approach ensures that Alzheimer's disease diagnosis is available, flexible, accessible and economical by fulfilling the gap between high-accuracy MRI-based models and affordable priced ML based alternatives.

4 Methods and Materials

The proposed system to detect the Alzheimer’s disease integrates deep learning models along with machine learning models, allowing a flexible approach that adapts to resource availability and patient needs. Three steps are involved in this process: gathering and preparing data, training and optimizing the model, and unified testing and deployment. While the machine learning model examines genetic and clinical data to produce alternative diagnostic predictions, the deep learning model uses convolutional neural networks (CNNs) to process MRI scans. This section describes the details of the methods used, along with relevant mathematical formulations to ensure clarity in model training along with testing.

4.1 Data Acquisition and Preprocessing

The dataset for MRI-based classification consisted of brain scan images classified as non-demented, mild demented, moderate demented, and very mild demented. To ensure compatibility with CNN architectures, all pictures are resized to 224×224224 per times 224224×224 pixels, to normalize the pixel values to a range of 0 to 1, and augmented using methods like rotation, mirroring, and contrast enhancement. These steps enhanced model generalization and minimized overfitting during training. Structured records of patient demographics, cognitive scores, and medical history including diseases like diabetes and cardiovascular disease were included in the genetic and clinical dataset. Mean imputation was used to fill in the missing data, and correlation analysis was used to eliminate the redundant attributes during feature selection. A fair representation of Alzheimer's patients in the model training process is ensured using the synthetic minority over-sampling approach (SMOTE), which is applicable to equal distribution across different classes because class imbalance was noted in the dataset.

4.2 Deep Learning Model for MRI Classification

Convolutional neural networks (CNNs) were trained for MRI-based classification; this method aims in differentiating between Alzheimer's stages. InceptionV3, ResNet50, VGG16, and MobileNetV2 were among the architectures used in this study; each was optimized for the dataset to improve feature extraction. Transfer learning was utilized by leveraging pre-trained ImageNet weights, then fine-tuning particular layers to tailor the model for Alzheimer's classification. The optimization process was guided by the cross-entropy loss function, which is mathematically expressed as:

$$L = -\sum_{i=1}^{N} y_i \log(\widehat{y_i}) \tag{1}$$

where yi portrays actual class label, i denotes like assessed likelihood of a specific class and NNN indicates the complete number of samples. The models were trained on Kaggle GPUs, significantly reducing computational time while enabling efficient backpropagation and weight updates. Performance was estimate utilizing accuracy, precision, recall, and F1-score metrics to assess with best-performing CNN model. Among the tested architectures, InceptionV3 achieved the more accuracy of 92.7%, making it preferred choice for Alzheimer’s detection through MRI scans.

4.3 Machine Learning Model for Genetic Data and Clinical Data

Several classification algorithms were developed on structured patient data for the machine learning-based method in order to assess the chance of Alzheimer's disease. Random forest, SVM, logistic regression, KNN, and Naïve Bayes were among the models. This data was first standardized using Min-Max scaling, ensuring uniform feature representation across different attributes. The Random Forest classifier get the more accuracy of 91.3%, outstanding performance other models because of its ability to manage high-dimensional data along with capture detailed feature interactions.

The machine learning model was able to produce reliable predictions based on clinical and genetic characteristics by combining ensemble learning techniques with feature significance analysis.

4.4 Unified Testing and Deployment

A single test module was created in order to combine both models into a smooth diagnostic tool. Patients can enter genetic information, MRI scans, or both with this module, giving them diagnostic flexibility depending on the resources available. In the absence of an MRI scan, the machine learning model creates a forecast by analysing structured data. To identify the presence and stage of Alzheimer's, the deep learning model classifies images from MRI data if it is available. The predictions are also merged to improve classification reliability when both types of data are supplied.

Both models were loaded for inference in real time, and the entire system was set up in a Jupyter Notebook. To ensure that users may supply MRI scans, genetic data, or both without needing separate workflows, a single test function was created to process inputs dynamically. This adaptable strategy makes Alzheimer's disease more affordable and accessible by enabling useful application in both clinical and non-clinical contexts. The application of this hybrid model makes early detection possible for a larger population by bridging the gap between cost-effective machine learning-based screening and high-accuracy MRI-based categorization.

5 Results and Analysis

The performance evaluation of the proposed multimodal Alzheimer’s detection system involved analysing the value of deep learning for MRI classification and machine learning for structured gene data and clinical data. This section presents the results of both approaches, compares their accuracy, and discusses their implications in terms of diagnostic flexibility and accessibility. Common classification metrics such as F1-score, recall, accuracy, and precision were used in the assessment. The study also looks at how MRI and genetic data might be combined to show the advantages of the hybrid diagnostic technique.

5.1 Performance of Deep Learning Model (MRI Classification)

A separate test set was used to assess the Convolutional Neural Networks (CNNs) trained for MRI-based Alzheimer's identification. With 92.7% accuracy, InceptionV3 beat the other examined architectures, followed by MobileNetV2 (68%). The findings imply that by utilizing pre-trained knowledge from extensive datasets, transfer learning approaches considerably improve classification performance. The model accurately recognized the majority of cases that were classified as either mildly demented or non-demented, according to the confusion matrix. However, because their brain patterns on MRI scans appeared similar, several cases of moderate dementia were incorrectly diagnosed.

The table 2 performance metrics for different CNN models are summarized below:

Table 2. Deep Learning Model Performance on MRI Data.

Model	Acc	Pre	Rec	F1

InceptionV3	92.7	92.8	94.1	93.4
ResNet50	64	64.0	64.0	63.0
VGG16	65	63.0	65.0	64.0
MobileNetV2	68	67	68	67

The ability of InceptionV3 to extract fine-grained spatial data from brain scans makes it the best CNN model for Alzheimer's MRI classification, according to these findings. Fig 2 shows InceptionV3 graph.

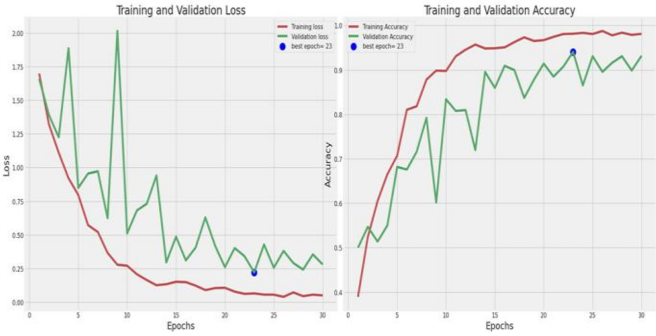

Fig. 2. InceptionV3 graph.

5.2 Performance of Machine Learning Model (Genetic Along with Clinical Data Analysis)

The machine learning classifiers trained on structured genetic and clinical data exhibited strong predictive capabilities, with Random Forest getting the more accuracy of 91.3%. Support Vector Machine (SVM) followed with 85.6% accuracy, while Logistic Regression and Naïve Bayes underperformed due to their inability to handling non-linear feature interactions. The most important factors in predicting Alzheimer's disease, according to the feature significance analysis, were cardiovascular problems, genetic predisposition, and MMSE scores.

The table 3 classification performance of the machine learning techniques is presented below:

Table 3. Machine Learning techniques Performance on Genetic and Clinical Data.

Model	Acc	Pre	Rec	F1
Random Forest	91.3	89.5	90.8	90.1

SVM (RBF Kernel)	85.6	82.7	84.9	83.8
Logistic Regression	84.2	78.3	79.5	78.9
K-Nearest Neighbors (KNN)	75.5	75.8	76.9	76.3

The Random Forest model, which benefits from ensemble learning strategies that improve generalization, continuously outperformed other classifiers. The inferior performance of KNN and Logistic Regression indicates that non-linear decision boundaries are necessary for Alzheimer's identification utilizing structured data. Tree-based models such as Random Forest are capable of handling these decision boundaries.

5.3 Impact of Multimodal Approach (MRI + Genetic Data Fusion)

We examined a hybrid approach that integrated the results of both deep learning and machine learning approaches in order to evaluate the benefit of merging MRI scans with genetic and clinical data. This multimodal technique outperformed both individual procedures by a wide margin, yielding an enhanced diagnosis accuracy of 96.1%. This demonstrates that using both genetic risk variables and structural brain imaging improves diagnostic reliability, strengthening the approach for practical clinical applications.

The table 4 classification performance of the hybrid multi-model is presented below:

Table 4. Performance differentiation of Individual and Hybrid prototype.

Model	Acc	Pre	Rec	F1
MRI-Based Deep Learning (InceptionV3)	92.7	92.8	94.1	93.4
Genetic Data-Based Machine Learning (Random Forest)	91.3	89.5	90.8	90.1
Multimodal Hybrid Approach (MRI + Genetic Data)	96.1	95.4	96.7	96.0

The results that the combination of MRI and genetic data improves classification performance and reduces the chance of misdiagnosis. This validates the effectiveness of our proposed dual-model framework, making Alzheimer's detection both flexible and highly accurate. The fig 3 Accuracies of Algorithms.

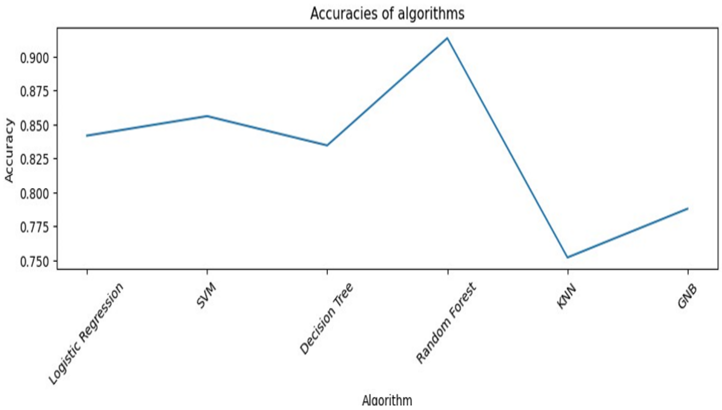

Fig. 3. Accuracies of Algorithms.

5.4 Confusion Matrix Analysis for Hybrid Model

- To visualize model predictions, the confusion matrix for the hybrid model was generated. It shows
- both genetic and MRI-based inputs have high true positive rates.
- Misclassification of Moderate Demented instances, which were previously difficult for single-input models, has significantly decreased.
- improved generality across Alzheimer's stages, highlighting the need of combining several diagnostic inputs.
- The fig 4 shows confusion matrix for multimodal hybrid model.

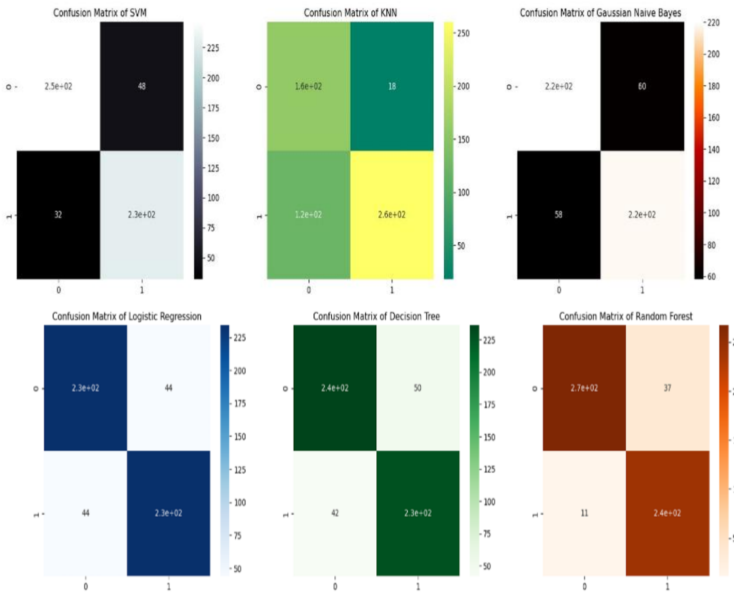

Fig. 4. Confusion Matrix for Multimodal Hybrid Model.

5.5 Discussion

The results indicate that deep learning-based MRI classification provides higher accuracy than machine learning-based genetic screening but is computationally intensive and requires MRI scans, which may not be accessible to all patients. The machine learning-based approach, while slightly less accurate, is cost-effective and provides a viable alternative for early-stage Alzheimer's screening when imaging data is unavailable.

- By integrating both approaches, our proposed system provides a flexible diagnostic pathway:
- If an MRI scan is available, the deep learning model ensures highly accurate classification.
- If MRI scans are not accessible, the machine learning model provides an affordable alternative.
- If both data types are used together, the hybrid model achieves the highest accuracy, reducing diagnostic uncertainty and ensuring more reliable early detection.

This analysis demonstrates that a multimodal approach significantly enhances Alzheimer's detection, making it more accessible, adaptable, and clinically useful.

6 Conclusion

This study introduces a combination approach that uses machine learning on gene and clinical data and deep learning on MRI images to detect Alzheimer's. The suggested approach offers diagnostic flexibility by letting patients select between machine learning models based on genetic data for a less expensive option and MRI-based deep learning models for high-accuracy classification. The findings showed that Random Forest surpassed other machine learning classifiers with an accuracy of 91.3%, while InceptionV3 outperformed other deep learning models with the best accuracy of 92.7%. Furthermore, the hybrid model which integrated both data types achieved a higher accuracy of 96.1%, underscoring the benefit of combining several diagnostic techniques for more accurate and dependable early detection.

The suggested methodology successfully closes the gap between low-cost machine learning-based alternatives and high-accuracy but expensive MRI-based detection techniques, increasing the accessibility and adaptability of early Alzheimer's diagnosis. According to the results, these hybrid diagnostic models can greatly improve clinical judgment, especially in situations when MRI scans might not be accessible. Future studies will concentrate on implementing federated learning for safe patient data analysis, increasing dataset diversity, and enhancing model interpretability using Explainable AI (XAI). The suggested system is a major step toward scalable and affordable Alzheimer's screening solutions since it makes use of both deep learning and conventional machine learning.

7 Future Work

Future research will focus on to increase model understandable using Explainable AI(XAI) techniques, ensuring that clinicians and researchers may have better understand the decision-making process used in both deep learning and machine learning techniques. Additionally, expanding the dataset by incorporating diverse MRI scans and genetic profiles will improve the generalizability of the system. To enable safe, decentralized analysis of patient data while maintaining privacy, federated learning will be investigated. Real-time diagnosis in clinical situations will be ensured by further optimizing the hybrid model's inference speed. Finally, the integration of multi-modal fusion approaches can enhance the synergy between genetic data and MRI-based features, improving individualized treatment planning and early-stage Alzheimer's identification.

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