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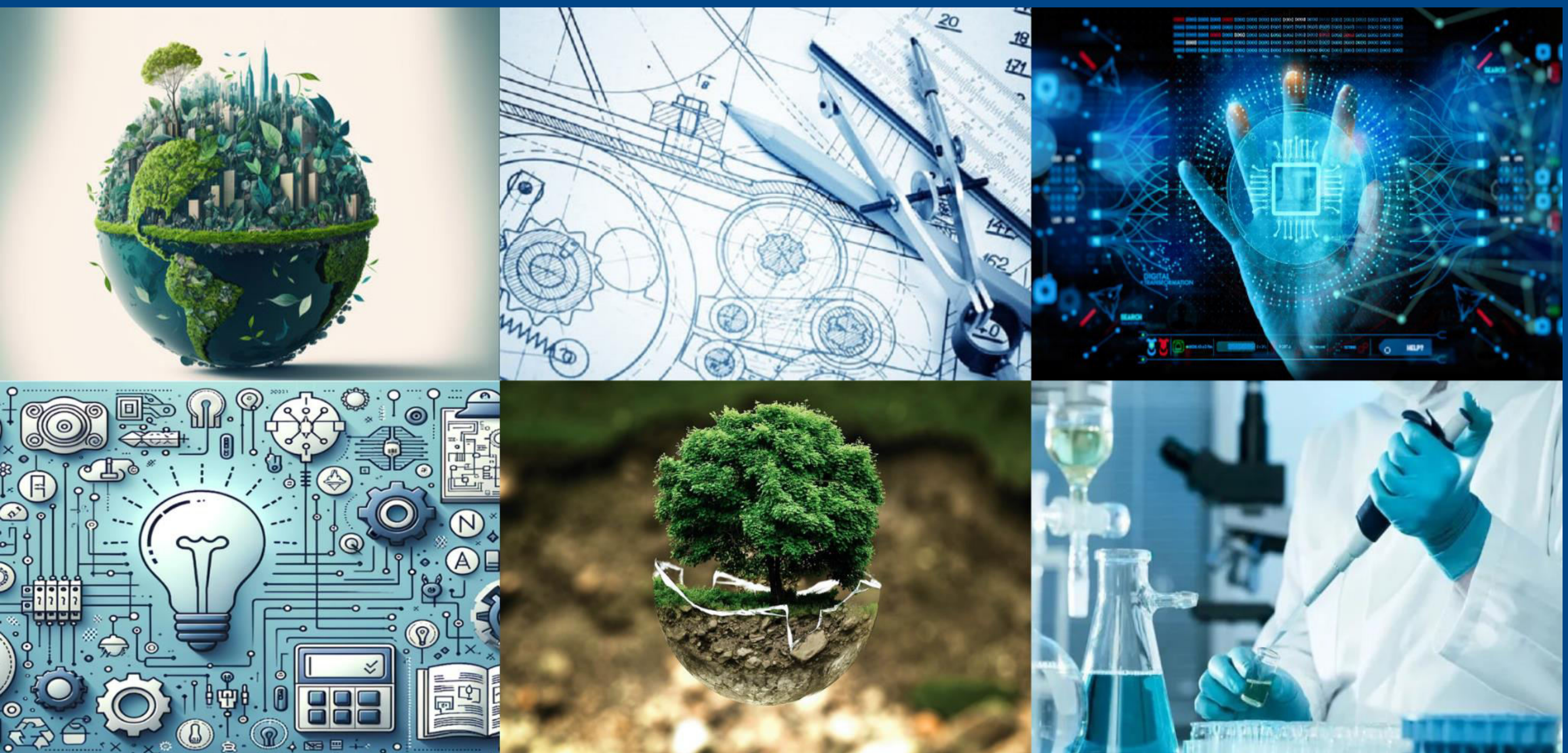

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Neurofusion: An AI-Based Hybrid Framework for Early Detection of Alzheimer's and Parkinson's Disease

T.Sam paul[1], Subashri V[2], Sagana B[3], Serah Anna Ajith[4]

Assistant Professor, Department of CSBS, R.M.D Engineering College, Chennai, India[1]

UG Scholar, Fourth Year, Department of CSBS, R.M.D Engineering College, Chennai, India[2]

UG Scholar, Fourth Year, Department of CSBS, R.M.D Engineering College, Chennai, India[3]

UG Scholar, Fourth Year, Department of CSBS, R.M.D Engineering College, Chennai, India[4]

ABSTRACT: Neurodegenerative diseases such as Alzheimer's disease (AD) and Parkinson's disease (PD) are progressive disorders requiring reliable early detection to improve clinical outcomes. Existing diagnostic systems often rely on single-modality analysis, using either structured clinical data or neuroimaging, which may limit diagnostic robustness. This paper presents NeuroFusion, a hybrid artificial intelligence–based framework integrating machine learning and deep learning for early neurodegenerative disease detection. The proposed system consists of two modules: (i) a machine learning classifier that analyzes demographic, clinical, and cognitive parameters for disease risk prediction, and (ii) a convolutional neural network (CNN) that processes brain MRI images to identify disease presence and severity. A standardized preprocessing pipeline including missing value handling, categorical encoding, and feature normalization is employed before model training. Among the evaluated models, Random Forest achieved superior classification performance. The framework is deployed as a web-based clinical decision support platform using Django and SQLite. The modular, fusion-ready architecture enhances scalability and supports multimodal integration for improved diagnostic reliability.

I. INTRODUCTION

A. Problem Definition:

Neurodegenerative diseases like Alzheimer's and Parkinson's are progressive and irreversible conditions that greatly affect cognitive and motor functions. Early detection is essential to slow disease progression and improve patient care. However, current diagnostic methods often rely on single-modality analysis, either clinical parameters or neuroimaging data, which can limit diagnostic reliability. This highlights the need for more comprehensive and integrated diagnostic approaches.

This paper presents NeuroFusion, a hybrid artificial intelligence-based clinical decision support framework that combines machine learning and deep learning for early detection. The first module applies machine learning algorithms such as Logistic Regression, Support Vector Machine, and Random Forest to analyze structured clinical and demographic data. A standardized preprocessing pipeline is implemented to handle missing values, encode categorical features, and normalize inputs. The second module employs a Convolutional Neural Network (CNN) to extract spatial features from brain MRI images, enabling disease classification and severity estimation.

Experimental evaluation using an 80–20 train-test split shows that the Random Forest classifier outperforms other traditional models, while the CNN-based image analysis enhances overall prediction performance by capturing complex neurological patterns. The framework is developed as a web-based platform using Django and SQLite, functioning as a clinical decision support system. By integrating multimodal data within a scalable architecture, NeuroFusion aims to improve diagnostic accuracy and reduce misclassification in the early detection of neurodegenerative diseases.

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B. Problem-Solving:

C. To tackle these issues, this paper introduces NeuroFusion, a combined artificial intelligence framework that merges machine learning and deep learning into a single architecture. The suggested system includes two interdependent components. The first component uses supervised machine learning techniques to evaluate structured data on demographics, lifestyle, medical background, and cognitive factors for predicting disease risk. The second component employs a Convolutional Neural Network (CNN) to analyze brain MRI scans and determine the presence and severity of diseases.

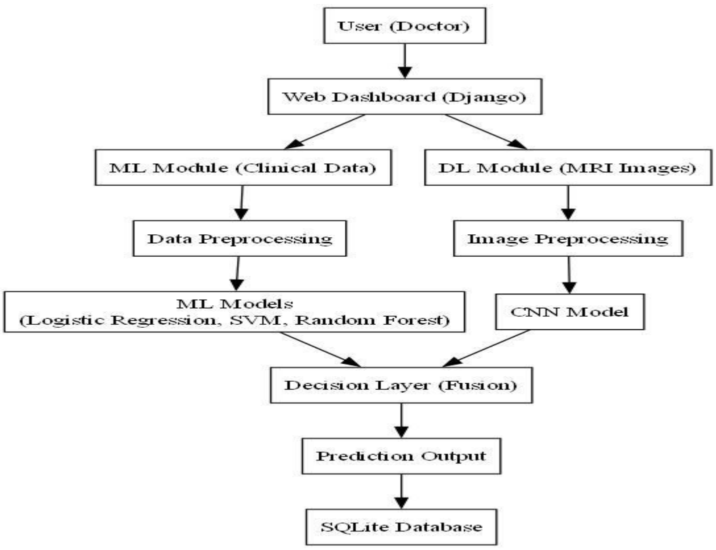
The architecture is structured to be modular and ready for integration, allowing for decision-level unification of predictions from both modalities. This multimodal strategy improves diagnostic reliability by merging risk-based evaluations with image-based validation. The framework is developed as a web-based clinical decision support system utilizing Django and SQLite, guaranteeing its practical use in healthcare settings.The main aim of NeuroFusion is to support healthcare providers rather than to take their place, by offering understandable, data-based diagnostic assistance for the early identification of neurodegenerative diseases.

II. LITERATURE SURVEY

No.	Paper Title	Key Findings	Remarks
1	Deep Learning for Alzheimer's Disease Classification Using MRI	CNN improves MRI-based classification accuracy	Limited to imaging modality
2	Machine Learning Techniques for Early Alzheimer's Detection	Random Forest and SVM perform well on structured clinical data	Does not include imaging data
3	Multimodal Learning for Neurodegenerative Disease Diagnosis	Combining clinical and imaging data improves robustness	Lacks deployment framework
4	Parkinson's Disease Detection Using ML and DL Approaches	AI-based detection using voice and imaging features	Focused on single disease modality
5	CNN-Based Brain MRI Analysis for Dementia Detection	Hierarchical feature extraction enhances accuracy	No clinical data integration

III. METHODOLOGY

A. SYSTEM ARCHITECTURE



The NeuroFusion framework proposed is crafted as a modular clinical decision support system that incorporates both machine learning and deep learning elements within a cohesive architecture. This system employs a top-down workflow that starts with user engagement and moves through concurrent analytical processes before producing ultimate predictions.The architecture is composed of five key layers: the user interface layer, the preprocessing layer, the analytical layer, the decision layer, and the storage layer.

In the initial stage, healthcare professionals engage with the system via a web-based dashboard built using the Django framework. This dashboard accommodates two kinds of inputs: structured clinical information and brain MRI images. The structured data pipeline analyzes demographic characteristics, lifestyle factors, medical history, and cognitive evaluation scores. These inputs undergo preprocessing steps that include addressing missing values, encoding categorical variables, and normalizing features. The resulting feature vector is then forwarded to supervised machine learning classifiers, such as Logistic Regression, Support Vector Machine, and Random Forest, for predicting disease risk.Simultaneously, the image-based pipeline processes uploaded MRI images. The images are resized and normalized prior to being input into a Convolutional Neural Network (CNN). The CNN conducts hierarchical feature extraction using convolutional and pooling layers, followed by fully connected layers to classify the presence and severity of the disease.

The results generated from both pipelines are sent to a decision layer. Although they are presently validated separately, the architecture allows for decision-level fusion, which means that structured risk scores and image-based classification outputs can be integrated to improve diagnostic reliability.Ultimately, the prediction outcomes are presented on the dashboard interface and saved in a SQLite database for record-keeping and future use. The modular design guarantees scalability and makes it easier to incorporate additional data types or sophisticated learning algorithms in the future.

B. ABOUT THE PROJECT

NeuroFusion is a framework that combines artificial intelligence with hybrid approaches to facilitate the early identification of neurodegenerative disorders, particularly Alzheimer's disease (AD) and Parkinson's disease (PD). This initiative merges machine learning and deep learning methods within a comprehensive, web-based clinical decision support platform.

The system consists of two main analytical components. The first component leverages supervised machine learning techniques to evaluate structured clinical and demographic data for predicting disease risk. The second component uses a Convolutional Neural Network (CNN) to examine brain MRI scans for detecting diseases and classifying their severity. The architecture is designed to be modular, allowing for future integration of structured and image-based predictions at the decision level.The system is developed using Python machine learning libraries and is deployed through the Django framework, utilizing SQLite for managing the database.

C. SCOPE OF THE PROJECT

The scope of NeuroFusion includes the development of an integrated diagnostic support platform capable of:

- Processing structured patient data for risk prediction
- Analyzing MRI images using deep learning models
- Providing interpretable prediction outputs for clinicians
- Supporting multimodal expansion through decision-level fusion

The system is designed to function as a clinical decision support tool rather than a fully autonomous diagnostic system. Although the present version concentrates on Alzheimer’s disease utilizing available clinical and imaging datasets, the architecture is adaptable and can be expanded to include Parkinson’s disease and other neurodegenerative conditions.

D. APPLICATION OF PROJECT

The proposed system can be applied in the following healthcare contexts:

- Early-stage neurodegenerative disease screening
- Clinical risk assessment support
- MRI-based diagnostic assistance
- Research environments for AI-based medical analysis

NeuroFusion is intended for medical practitioners, such as neurologists and clinicians, to facilitate decision-making based on evidence. The platform delivers organized risk scores and image-based classification results, assisting in diagnostic assessments and patient oversight.

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A. EXISTING SYSTEM

Current diagnostic methods for neurodegenerative diseases generally depend on either standard clinical evaluations or single-modality artificial intelligence techniques.Traditional clinical methods include cognitive assessments, physical examinations, and the interpretation of neuroimaging by specialists. While these approaches are effective, they can be labor-intensive and rely heavily on the availability of experts.

Modern AI-driven systems typically concentrate on either machine learning applied to organized clinical datasets or deep learning utilized for MRI scans. However, these unimodal solutions may not effectively address the complex, multidimensional characteristics of neurodegenerative conditions. Moreover, many of these applications remain in the experimental phase and do not integrate into practical clinical platforms.

B. PROPOSED SYSTEM

The NeuroFusion system aims to overcome the shortcomings of current methods by combining machine learning and deep learning within a cohesive architecture prepared for fusion. The structured data module analyzes demographic, lifestyle, medical history, and cognitive evaluation information by employing supervised classification techniques such as Logistic Regression, Support Vector Machine, and Random Forest.The deep learning module employs a Convolutional Neural Network to derive hierarchical features from MRI scans and determine the presence and severity of diseases.

In contrast to existing unimodal systems, NeuroFusion is built for multimodal integration through decision-level fusion, which enhances diagnostic reliability. Additionally, the framework is implemented as a web-based platform using Django and SQLite, making it well-suited for real-world healthcare settings.

IV. USAGE

The NeuroFusion framework is a web-based system for clinical decision support that facilitates structured data analysis and MRI-based image classification via a unified dashboard interface. The system functions through two separate analytical workflows.

A. Utilization of the Machine Learning Module

In the machine learning module, healthcare practitioners enter structured patient data through an online form. The input criteria encompass demographic details, lifestyle factors, medical history, and scores from cognitive assessments.
After submission, the system carries out the following processes:

- Validation and preprocessing of inputs
- Encoding and normalization of features
- Execution of model inference using the trained classifier

B. Utilization of Deep Learning Module

The deep learning module aids in the analysis of MRI images. Users can upload a brain MRI image through the dashboard interface.
The system executes the following processes:

- Resizing and normalizing the image
- Extracting features utilizing the Convolutional Neural Network
- Classifying the presence and severity of disease
- Providing the predicted class along with a confidence score

The results offer diagnostic insights based on images, including classification of disease stages where applicable.

C. Integrated Workflow

While each module operates on its own, the framework is designed to accommodate future integration of decision-level fusion. In a clinical context, a healthcare provider might first assess risk using structured data and then validate diagnostic results through MRI image examination.The system aims to aid clinicians by delivering clear, data-informed conclusions. It is not intended to act as an independent diagnostic tool but rather as a complementary resource to improve clinical decision-making.

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V. FEATURES

The NeuroFusion framework features several key technical components:
A. Multimodal Architecture
This system merges the analysis of structured clinical data with MRI-based image classification into a cohesive framework, facilitating complementary learning from diverse data sources.

B. Hybrid ML–DL Integration
It integrates supervised machine learning techniques (including Logistic Regression, SVM, and Random Forest) with a Convolutional Neural Network (CNN) for image evaluation, enabling both statistical pattern recognition and spatial feature extraction.

C. Fusion-Ready Design
The architecture allows for decision-level fusion of risk scores from machine learning and classification outputs from deep learning to improve diagnostic reliability.

D. Uniform Preprocessing
A standardized preprocessing pipeline that addresses missing values, encodes categorical data, and normalizes features guarantees data consistency and reproducibility.

E. Online Deployment
The system is developed with Django and SQLite, offering a scalable interface for clinical decision support tailored for healthcare professionals.

VI. IMPACT OF UNADDRESSED EARLY DETECTION

Neglecting the early detection of neurodegenerative disorders like Alzheimer’s disease and Parkinson’s disease can result in diagnoses at advanced stages, where neuronal damage becomes mostly irreversible. Delayed recognition diminishes the effectiveness of treatments and accelerates both cognitive and motor decline, significantly impacting the quality of life for patients.

Additionally, relying solely on single-modality diagnostic methods may heighten the risk of misclassification, further delaying necessary interventions. From a healthcare standpoint, managing late-stage cases leads to increased medical expenses, greater resource consumption, and added burden on caregivers.Thus, effective and scalable frameworks for early detection are crucial to enhance clinical outcomes and lessen the long-term effects of these diseases.

VII. EXPERIMENTAL FRAMEWORK

A. Dataset Overview
The evaluation of the NeuroFusion framework was carried out using two separate datasets: one structured clinical dataset and one MRI image dataset.The clinical dataset includes demographic information, lifestyle factors, medical history details, cognitive assessment results, and features related to symptoms. The target variable indicates disease diagnosis in a binary format (0 = Non-diseased, 1 = Diseased). Before training the model, the dataset was divided into training and testing sets using an 80–20 split to ensure an unbiased assessment.

For the deep learning component, labeled brain MRI images were used. The dataset encompasses various diagnostic categories that reflect different levels of disease severity. Images were resized to standardized spatial dimensions and normalized before CNN training to maintain consistent feature representation.
B. Mathematical Representation

Structured Clinical Input Representation
Let the structured input feature vector be represented as:
$X = [x1, x2, x3, ..., xn]$
where xi denotes individual clinical features.

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The supervised classification model predicts the output label as:
$\hat{y} = f(X)$

Logistic Regression Model
For Logistic Regression, the probability estimation is given by:
$P(y = 1 \mid X) = 1 / (1 + e^{-(w^T X + b)})$

where:
- w represents the weight vector
- b denotes the bias term
- $w^T X$ is the dot product between weights and input features

Deep Learning Module (CNN + Softmax)
In the deep learning module, the Convolutional Neural Network (CNN) extracts hierarchical feature maps from input MRI images.
The final classification layer applies the Softmax function:
$\hat{y} = \mathrm{Softmax}(Wx + b)$
where:
- W and b are learnable parameters of the fully connected layer
- Softmax converts raw scores into probability values

Performance Metrics
Model performance is evaluated using standard classification metrics derived from the confusion matrix:
- True Positive (TP)
- True Negative (TN)
- False Positive (FP)
- False Negative (FN)

The evaluation metrics are defined as follows:

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

Precision
Precision = TP / (TP + FP)

Recall
Recall = TP / (TP + FN)

F1-Score
F1-Score = (2 × Precision × Recall) / (Precision + Recall)

VIII. RESULT AND DISCUSSION

The machine learning module was assessed using an 80–20 train–test split with Logistic Regression, Support Vector Machine (SVM), and Random Forest classifiers. Among these models, Random Forest showed the best classification performance on structured clinical data. Analysis of the confusion matrix revealed high true positive and true negative rates, coupled with a small number of misclassifications. While a few false negatives were detected, the overall findings validate the effectiveness of ensemble learning in capturing nonlinear relationships across diverse medical features. The deep learning module, which utilized a Convolutional Neural Network (CNN), successfully classified MRI images by identifying hierarchical spatial features linked to neurodegenerative progression. The predictions based on images enhance the risk assessment of structured data by revealing anatomical abnormalities that may not be captured by clinical parameters alone.The results confirm that it is possible to combine machine learning and deep learning into a cohesive framework. The modular design additionally facilitates decision-level integration, which could improve diagnostic reliability and lower the chances of misclassification in practical clinical environments.

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IX. CONCLUSION

This study introduced NeuroFusion, a combined artificial intelligence framework designed for the early identification of neurodegenerative conditions, particularly Alzheimer's disease and Parkinson's disease. The suggested system merges machine learning for predicting clinical risks with deep learning for classifying MRI images, all within a single, web-based architecture. Experimental results showed that the Random Forest algorithm outperformed other traditional classifiers in analyzing structured data, while the Convolutional Neural Network successfully detected disease patterns in MRI scans. The framework's modular and easily integrable design improves scalability and allows for the incorporation of various data types, thereby enhancing diagnostic reliability. NeuroFusion aims to serve as a clinical decision support tool, aiding healthcare practitioners rather than substituting for their expertise. The findings suggest that hybrid AI frameworks present a valuable strategy for the dependable and scalable early detection of neurodegenerative diseases.

X. FUTURE WORK

Future efforts will concentrate on implementing decision-level fusion between the machine learning and deep learning components to improve diagnostic reliability and minimize false negatives. Incorporating larger and more varied clinical and imaging datasets will further enhance the generalization and dependability of the model. Furthermore, advanced deep learning frameworks, such as transfer learning and attention-based networks, may be integrated to boost performance in MRI classification.

The framework could also be expanded to encompass other neurodegenerative diseases and multimodal data types, including voice analysis and gait observation for the detection of Parkinson’s disease. We will aim for deployment in actual clinical settings with prospective validation to assess system performance in real healthcare environments.

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