

MULTIMODAL EXPLAINABLE-AI FRAMEWORK FOR STROKE AND TRAUMATIC BRAIN INJURY DETECTION AND PROGNOSIS USING IMAGING AND CLINICAL DATA IN MACHINE LEARNING

A. PRABHA

PG STUDENT, DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING, THE KAVERY ENGINEERING COLLEGE, MECHERI, SALEM DISTRICT, TAMIL NADU, INDIA, EMAIL: prabhaalagesan@gmail.com

S. VELAN

PG STUDENT, DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING, THE KAVERY ENGINEERING COLLEGE, MECHERI, SALEM DISTRICT, TAMIL NADU, INDIA, EMAIL: velansenthilkumar23@gmail.com

S. JEEVITHA

PG STUDENT, DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING, THE KAVERY ENGINEERING COLLEGE, MECHERI, SALEM DISTRICT, TAMIL NADU, INDIA, EMAIL: jeevisure7229@gmail.com

DR. M. BALAMURUGAN

HEAD OF THE DEPARTMENT, DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING, THE KAVERY ENGINEERING COLLEGE, MECHERI, SALEM DISTRICT, TAMIL NADU, INDIA, EMAIL: balacrazy.it@gmail.com

V. RAMYA

ASSISTANT PROFESSOR, DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING, THE KAVERY ENGINEERING COLLEGE, MECHERI, SALEM DISTRICT, TAMIL NADU, INDIA, EMAIL: venkatachalamramya@gmail.com

DR. A. VANITHA

ASSOCIATE PROFESSOR, DEPARTMENT OF MCA, PAAVAI ENGINEERING COLLEGE, PACHAL, NAMAKKAL, TAMIL NADU, INDIA, EMAIL: vanitarget@gmail.com

Abstract

This research presents a Multimodal Explainable-AI Framework for the detection and prognosis of Stroke and Traumatic Brain Injury (TBI) using integrated imaging and clinical data. The proposed model leverages machine learning and deep learning techniques to enhance diagnostic accuracy and interpretability. Two datasets are employed: the Stroke Risk Prediction dataset containing patient clinical attributes and the TBI MRI Segmentation dataset providing brain imaging data. Preprocessing is performed using the Gaussian Wavelet Transform (GWT) to reduce noise and enhance feature clarity in MRI scans. Stroke and Traumatic Brain Injury (TBI) are employed for efficient feature extraction from multimodal data, capturing both spatial and textural patterns critical for diagnosis. The extracted features are classified using a Generalized Regression Neural Network (GRNN), which ensures fast training and robust generalization. To ensure transparency, Explainable-AI techniques are incorporated for interpretability of model decisions. Performance is evaluated using metrics such as accuracy of 0.91%, precision of 0.94%, recall of 0.90 %, F1-score of 0.91%, and ROC-AUC of 0.98%, demonstrating superior diagnostic capability compared to traditional models. This framework provides a powerful, interpretable decision-support system for clinicians, aiding early detection and prognosis assessment in stroke and TBI patients, ultimately contributing to improved treatment outcomes and patient.

Keywords: Stroke and Traumatic Brain Injury (TBI), Gaussian Wavelet Transform (GWT), Generalized Regression Neural Network (GRNN), accuracy, precision, recall, F1-score, and ROC-AUC

1. INTRODUCTION

The framework presented in their study [1] aimed to predict recovery post-stroke using multimodal data to utilize explainable AI and highlight the significance of combining clinical and imaging data [2] proposes a multimodal predictive model of spinal cord injury based on explainable AI systems, emphasizing the importance of transparent AI systems in neuroprognosis. [3] also showed that interpretable ML methods may be used to effectively correlate brain imaging with survival data, and improve clinical interpretability and trust. Explainable AI has emerged as a vital part of clinical ML systems, providing transparency and accountability in the decision-making process [4]. summarized several types of XAI used in biomedical modeling, which would help enhance the reliability and clinical acceptability of AI-based systems. In traumatic brain injuries, [5] developed ML algorithms to predict the

prognosis with a good performance on a variety of clinical variables. The incorporation of imaging and clinical data has been confirmed to have a substantial impact on the diagnostic and prognostic outcomes [6] [7]. Applied automated ML to stroke recovery and recovery prediction based on MRI and patient clinical characteristics [8]. Used multimodal datasets to predict hospital stay duration and prognosis in patients with TBI. Similarly, [9] developed a predictive model of functional recovery following TBI, demonstrating the benefits of hybrid clinical-imaging features. These findings were strengthened in a review conducted [10] that suggested that ML and XAI are transformative tools that aid in enhancing neurological outcome predictions.

1.1 Objective of the Study

- To utilize the Stroke Risk Prediction data set comprising of patient clinical factors and the TBI MRI Segmentation data set comprising of brain images to support effective diagnosis and prognosis of Stroke and TBI, it is important to make sure that the input is properly multimodal.
- To use Gaussian Wavelet Transform (GWT) to reduce noise and improve the performance of MRI scans by enhancing the quality of imaging data to feed future analysis.
- To derive the most important spatial and textual information about multimodal data, the patterns in clinical qualities and imaging data needed to accurately identify and prognosticate Stroke and TBI.
- To utilize the Generalized Regression Neural Network (GRNN) to rapidly train, have strong generalization, and correctly classify the extracted features.
- To evaluate the framework on the basis of evaluation measures, including the accuracy, precision, recall, F1-score, and ROC-AUC, showing a better diagnostic performance and higher interpretability in relation to the traditional frameworks.

1.2 Contribution of the work

- Combines both clinical and imaging findings for robust stroke and TBI detection, improving diagnostic sensitivity.
- In introducing the GWT, noise is suppressed and feature details of MRI images are sharpened for better input data in our method.
- Learns important spatial and textural patterns in multimodal data for effective and robust characterization of stroke and TBI.
- Improved classification performance, dependable generalisation, and quick training are achieved by implementing a generalised regression neural network.
- Enables doctors to make well-informed judgements and evaluate prognoses early by using Explainable-AI techniques to bring transparency to model decisions.

1.3 Organization of the paper

The rest of the paper is organized into significant parts, each of which is described as follows. Section II lists the research projects on Multimodal Explainable-AI Framework for Stroke and Traumatic Brain Injury Detection and Prognosis using Imaging and Clinical Data in machine learning, completed by various authors. The suggested method's workflow is defined in Section III, and the Results and performance analysis of the Multimodal Explainable-AI Framework for Stroke and Traumatic Brain Injury Detection and Prognosis using Imaging and Clinical Data in machine learning are presented in Section IV. Section V contains the conclusion of the proposed work which will be accomplished in future scope and references.

2. RELATED WORK

Cerasa et al., (2022) This paper compares machine learning models to conventional statistical models used to predict the outcome of brain injury. ML models were more accurate and flexible using patient clinical and neuroimaging data. The study shows the value of higher level algorithms that identify patterns that are ignored by the traditional approaches. Findings indicate that the ML is more predictive reliable in prognosis of neurorehabilitation.

Yu et al., (2023) The authors proposed a multimodal machine learning model with multi-modal MRI radiomics that is used to predict the prognosis of ischemic stroke. It integrates pictorial and clinical characteristics to determine the potential of recovery in patients. The model was found to be extremely accurate in relation to outcomes prediction in comparison to conventional techniques. The benefit of this method is that it increases individualized stroke planning.

Pan et al., (2025) It is a study that presents an interpretable machine learning model to detect CT abnormalities in mild traumatic brain injury. The best features can be identified to pick the best features that make it transparent and clinically relevant. The model assists the physicians in comprehending diagnostic decisions as well as enhancing accuracy. Findings support its early and explainable detectability of TBI.

Chen et al., (2025) Predictive ML model, the proposed model employs an emergency clinical data to predict in-hospital mortality within a 3-day period of stroke and trauma patients. It examines vital signs, lab findings and demographics to make a quick evaluation. The system facilitates early intervention and prioritization of resources in emergency care. There are high predictive power and reliability findings.

Mac Donald et al., (2025) The study concentrates on the neuroimaging description of acute brain traumatic injury to be used clinically. It offers standardized recommendations of the 2024 TBI classification project of the NIH.

The paper focuses on enhanced diagnostic imaging guidelines to frontline practitioners. These are rules that lead to a standard in TBI evaluation and data interpretation.

Xia et al., (2025) The research profile created a predictive nomogram that integrated the MRI white matter hyperintensity radiomics characteristics with clinical variables in prediction of 90-day outcomes in a cohort of patients under acute ischemic strokes. The combined model was trained using Matlab and ITK- SNAP on image segmentation and SVM on training the model respectively. The suggested method was better in comparison with single models, achieving an AUC of 0.939 with high sensitivity and specificity.

Nidamanuri et al., (2025) The article presents a deep learning model based on the application of MRI data to forecast mild versus severe traumatic brain injury. To achieve a better accuracy, shorter training time was done with a residual convolutional neural network with transfer learning in a dataset of 204 TBI patients. The model demonstrated high accuracy of 93.31% and 100% severity per the severities and mild cases respectively with very strong potential of an early diagnosis and clinical decision support.

Li et al., (2025) The analysis was carried out to show clinical information on one thousand four hundred and eighty-four TBI patients by showing the likelihood of post-traumatic cerebral infarction with the aid of machine learning where this data showed that the main factors that dictated such a condition were age, brain contusions, and glucose levels. Logistic regression had an AUC of 0.821 which was the best and the specificity was high. Interpretability was offered by SHAP values, which helps to provide an individual approach to assessing risks and designing treatment.

Issaiy et al., (2025) In this review, 24 articles on ML and DL models to predict hemorrhagic transformation following an acute ischemic stroke were incorporated. Gradient boosting and CNNs also worked best with median AUC of 0.91 surpassing the traditional scoring among others. These models facilitate the improvement of prediction, increase the advantages of clinical decision-making in stroke management.

Abujaber et al., (2025) This paper adopted machine learning models and SHAP analysis to forecast 90-day prognosis and in-hospital mortality among hemorrhagic stroke patients. The best prediction of prognosis was achieved with the help of random forest, and prediction of mortality by using logistic regression was the most appropriate as NIHSS score and admission location were the most announced predictors. The results suggest that first stroke severity and treatment in special stroke units are of paramount importance to achieve more precise expectancy models and enable more effective clinical decision-making.

Table 1 Comparison of AI Models for Stroke/TBI Detection: Features, Interpretability, and Limitations

Ref . No	Model	Data augmentation	Predictive model	Interpretability	XAI-driven deep learning	Limitations
21	Random Forest, XGBoost, SVM	X	✓	X	X	Retrospective dataset; limited generalizability across hospitals
22	Multimodal CNN, Transformer	✓	✓	X	X	Need for larger external validation; limited clinical interpretability
23	Ensemble CNN with XAI (Grad-CAM)	✓	✓	✓	✓	Limited dataset size; model complexity affects deployment
24	CNN with clinical variables	X	✓	X	X	Lack of external testing; data imbalance
25	Deep Learning + Radiomics (3D CNN)	✓	✓	X	X	Single-center study; limited generalization
26	Various AI models (review)	X	X	X	X	No experimental validation; review-based findings
27	Machine Learning (Random Forest, SVM)	X	✓	X	X	Retrospective data; no deep interpretability
28	CNN on non-contrast CT	X	✓	X	X	Lack of multicenter data; possible selection bias

29	Machine Learning (SVM, kNN, Decision Tree)	✓	✓	✗	✗	Manual preprocessing; limited interpretability
30	Review of AI methods	✗	✗	✗	✗	Conceptual review; no implementation

The table 1 provides an overview of recent research that identifies different machine learning and deep learning models used in clinical predictions related to the brain. The most popular models used in the majority of studies were predictive models, i.e., the Random Forest, CNN, and Transformer, and multimodal data were used in some of them. There were studies that augmented data to enhance the robustness of the models, especially in multimodal and radiomics-based models. Nevertheless, there was little interpretability and XAI-inspired deep learning algorithms, and Grad-CAM was only used in a few studies to explain their results. The general constraints of these works include small or retrospective datasets, not externally validated, generalizability, and low clinical interpretability, which underscores the need to have more explainable and scalable methods.

3. PROPOSED METHODOLOGY

The suggested methodology is a Multimodal Explainable-AI Framework which combines imaging and clinical data to detect and prognose TBI and stroke shown in figure 1. The pre-processing of the clinical characteristics of the Stroke Risk Prediction dataset and the brain MRI scan of the TBI Segmentation dataset involves the application of the Gaussian Wavelet Transform (GWT) in noise reduction and the height of features. Multimodal feature extraction obtains a spatial and textural pattern which can be used in diagnosis. These features are extracted and then classified with the help of the Generalized Regression Neural Network (GRNN) which guarantees the high speed of training and good generalization. The explainable-AI methods are added to provide interpretations to model choices, which will make it even more transparent. Accuracy, precision, recall, F1-score, and ROC-AUC measures of the performance of the framework are shown to have better diagnostic ability and level of reliability and interpretable decision-support tool to be used in the early detection and prognosis of stroke and TBI patients.

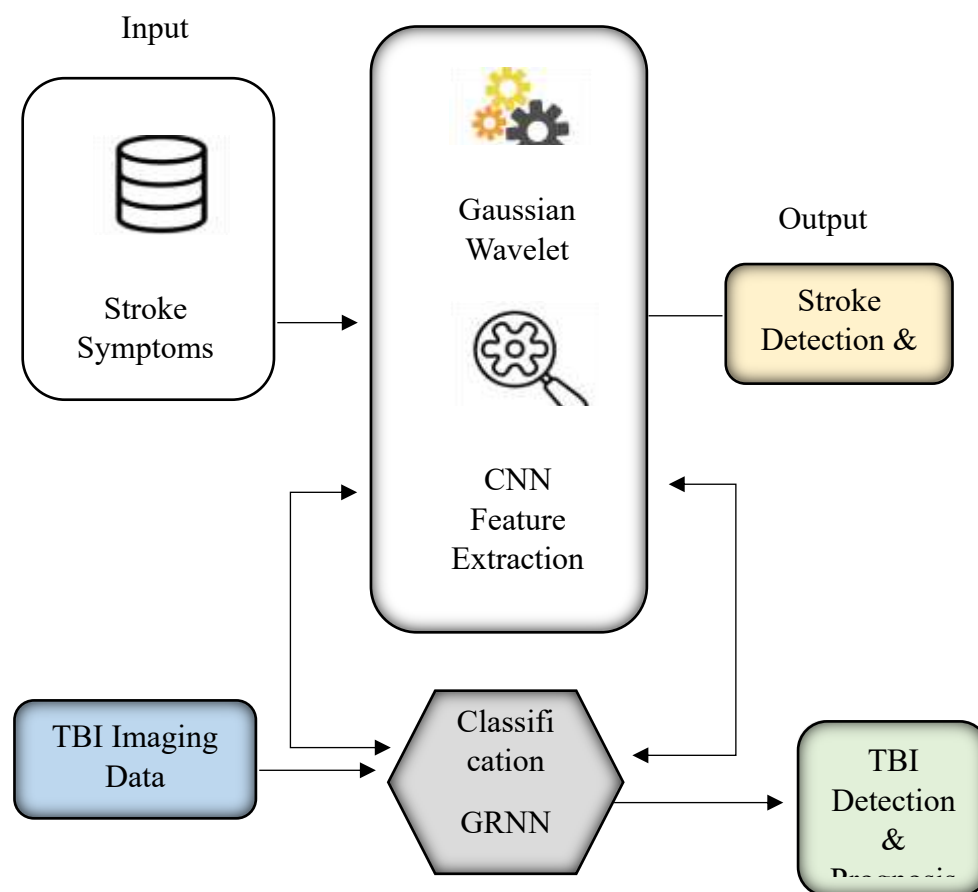


Figure 1 Block diagram of Multimodal AI Framework for Stroke and TBI Detection

3.1 Stroke Risk Prediction Dataset

The Stroke Risk Prediction Dataset is a medically curated dataset developed to facilitate predictive modeling of stroke occurrence using both classification and regression approaches. It contains a balanced set of records, with 50% representing individuals at risk and 50% not at risk, ensuring unbiased model training. The dataset integrates

demographic information, particularly age, along with a comprehensive set of binary symptom indicators, including cardiovascular, neurological, and sleep-related features such as chest pain, irregular heartbeat, dizziness, fatigue, snoring, and high blood pressure. Target variables include a binary stroke risk label and a continuous probability estimate. Features and distributions are derived from established clinical literature, medical guidelines from the American Stroke Association, and insights from authoritative sources such as Mayo Clinic, Cleveland Clinic, Harrison's Principles of Internal Medicine, and WHO stroke reports. Symptom severity and age are incorporated to enhance predictive accuracy. This dataset is optimized for machine learning and deep learning frameworks, supporting applications in classification, regression, and explainable AI, making it a robust tool for developing clinically relevant stroke prediction models.

3.2 TBI MRI Segmentation Dataset

TBI MRI Segmentation Dataset includes magnetic resonance images of patients with traumatic brain injury and segmentation masks, which indicate injured areas of the brain. The dataset will be useful in the creation of deep learning models that have the ability to detect and outline areas of injuries automatically, and thus aid in the clinical evaluation and diagnosis. It is specifically applicable to image segmentation with the convolutional neural networks (CNNs) and special architectures like U-Net. The data offers annotated MRI information, allowing a accurate learning of structural brain abnormalities, research in automated TBI detection and advanced medical image analysis. https://www.kaggle.com/datasets/theerayut/tbi-mri-segmentation?utm_source=chatgpt.com

3.3 Preprocessing using Gaussian Wavelet Transform

Preprocessing is the first and most important stage in any multimodal explainable-AI framework, and it is especially important for the identification of traumatic brain injury and stroke. Before feeding the input data into machine learning models, it attempts to enhance its quality and remove unwanted noise. The Gaussian Wavelet Transform (GWT) is used to the imaging MRI or CT images during this procedure. In order to eliminate noise while preserving crucial structural details like tissue borders and lesions, GWT splits the picture into many scales using Gaussian-based wavelets. In order to provide accurate and comprehensible analysis, this technique improves contrast, removes artifacts, and ensures that the model focuses on patterns that are pertinent to medicine.

Table 2: Preprocessing using Gaussian Wavelet Transform

Equation No	Mathematical Expression	Description
1.	$W(a, b) = \int f(t) \psi_{a,b}(t) dt$	Calculates the wavelet coefficients by multiplying the input signal $f(t)$ with the Gaussian wavelet function.
2.	$\psi_{a,b}(t) = \frac{1}{\sqrt{a}} \psi\left(\frac{t-b}{a}\right)$	Determines the wavelet scaling factor (a) and the translation parameter (b).
3.	$\psi(t) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{t^2}{2\sigma^2}}$	Represents the Gaussian wavelet used for smoothing and noise suppression.
5.	$f'(t) = \int W'(a, b) \psi_{a,b}(t) da db$	Reconstructs the processed signal or image from filtered coefficients.

The table 2 indicates the main stages of pre-processing with the Gaussian Wavelet Transform (GWT) in stroke and traumatic brain injury detection. It starts with the calculation of wavelet coefficient where the input signal or image is convolved with the Gaussian wavelet to extract the spatial and frequency information. The wavelet is scaled and translated in order to analyze the features on the various resolutions, and the Gaussian wavelet is used to provide a smooth and edge-preserving wavelet. This is achieved by denoising with thresholding to discard irrelevant coefficients, and lastly, signal reconstruction is used to construct the denoised image. Collectively, the steps will result in a quality, structured data to be used in machine learning-based diagnoses and explainable analysis.

3.4 CNN-Based Feature Extraction for Stroke and TBI Detection

The feature extraction is conducted based on a Convolutional Neural Network (CNN) to extract meaningful patterns automatically on brain imaging data. The CNN uses convolutional layers to identify edges, textures, and other structural abnormalities in stroke or a traumatic brain injury. Layers of pooling help save space and maintain important information, as well as increase the efficiency of computations. Activation functions bring in non-linearity, which allows the network to acquire complex representations. The features that are extracted are small differences in the brain tissue and the lesion areas, which are used together with clinical data. This integration enhances the accuracy of the diagnosis, and explainable-AI methods display the regions of interest, which should be interpreted by clinicians shown in figure 2.

$$F_{i,j}^k = \sum_m \sum_n I_{i+m,j+n} \cdot K_{m,n}^k + b^k \quad (1)$$

The equation (1) represents the core operation in a Convolutional Neural Network (CNN). Here, I denotes the input image, k is the convolutional filter (or kernel) of the k th feature map, and b^k is the bias term. The convolution process involves sliding the kernel over the image and computing the weighted sum of pixel values within the receptive field. This operation extracts important spatial features like edges, textures, and intensity variations. The output feature map Fk highlights these learned features, which form the foundation for deeper pattern recognition in CNN-based models.

$$A_{i,j}^k = \max(0, K_{i,j}^k) \quad (2)$$

The equation (2) is the Rectified Linear Unit (ReLU) activation which is an important step in Convolutional Neural Networks (CNNs). Following convolution, this function makes the feature map non-linear by casting any negative values in the feature map to zero. This assists the network to acquire intricate and non-linear connections in the data. ReLU also offers faster training because it does not experience the vanishing gradient issue that deep networks have. Consequently, the stimulated feature map Ak identifies key aspects of the image, allowing the CNN to concentrate on the significant patterns in the form of edges, shapes, and textures.

$$P_{i,j}^k = \max_{(m,n) \in R} A_{i+m,j+n}^k \quad (3)$$

The equation (3) is the max pooling process of a Convolutional Neural Network (CNN). In this process, a small region R (such as 2×2 or 3×3) slides over the activated feature map Ak and the maximum value within each region is selected to form the pooled feature map Pk . This operation shrinks the data spatially whilst preserving the most significant features which causes the model to be less computationally expensive and less sensitive to small image perturbations or noise. Translation invariance is also obtained with the assistance of max pooling, which enhances the strength and generalization of the CNN.

$$y = \sigma(W \cdot x + b) \quad (4)$$

The equation (4) represents the fully connected (dense) layer operation in a Convolutional Neural Network (CNN). Here, x is the flattened input vector containing extracted features, W is the weight matrix, b is the bias term, and σ is the activation function (such as ReLU or sigmoid). It is a linear transformation with a nonlinear activation that transforms the learnt features into a decision space. It fuses the advanced features of the past convolution and pooling layers so that the model could identify the intricate patterns and carry out the classification procedures including the detection of a stroke or traumatic brain injury areas.

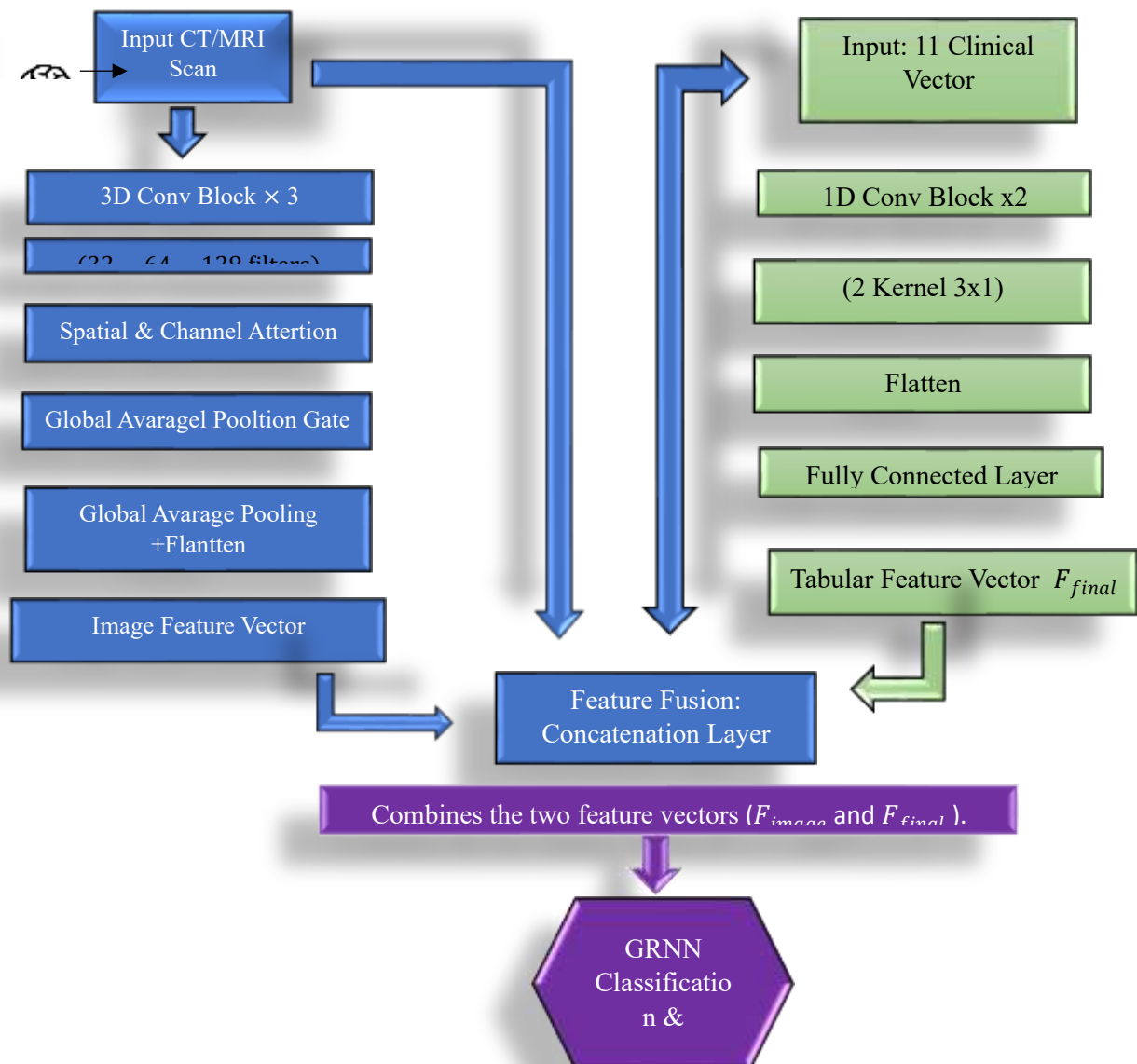


Figure 2 Convolutional Neural Network (CNN) Architecture

$$\hat{y}_i = \frac{e^{y_i}}{\sum_j e^{y_j}} \quad (5)$$

The equation (5) represents the Softmax activation function, commonly used in the final layer of a Convolutional Neural Network (CNN) for multi-class classification. This function converts the raw output values y_i (also called logits) into normalized probabilities that sum to one. Each output $\hat{y}_i$ indicates the probability that the input image belongs to class i . Exponential operation focuses on greater logits, whereas the denominator normalizes the operation of all classes. Softmax is used in stroke and traumatic brain injury detection to allow the model to place probabilistic confidence values on each diagnostic category to increase the interpretability of the decision and improve the classification accuracy.

3.5 Classification using Generalized Regression Neural Network (GRNN)

The specific discriminant or classifier of the fused multimodal features is the Generalized Regression Neural Network (GRNN). GRNN is a single feed-forward map and is modeled by a radial basis function (RBF) kernel in the pattern layer, which calculates the similarity of an input feature vector with training examples in storage. This is followed by the output layer where the weighted average is carried out with the weights being formed as a result of the RBF layer and controlled by a very important smoothing parameter (σ). This approachology is the best at non-linear, highly precise, function approximation, and is thus capable of providing definitive Stroke/TBI detection (classification) as well as continuous prognostic scores (regression) not only with rapidity and transparency.

$$\psi_i(x, x_i) = \exp\left(-\frac{D_i^2(x, x_i)}{2\sigma^2}\right) \quad (6)$$

The equation (6) represents a radial basis function (RBF), commonly used in machine learning, neural networks, and kernel methods. Here, $D_i(x, x_i)$ denotes the distance between the input point x and the center x_i , often measured using the Euclidean distance. The parameter σ controls the width or spread of the function, determining how strongly the influence of a training point extends in the feature space. The exponential term ensures smoothness, producing high values when x is close to x_i and decreasing rapidly as the distance increases.

$$y(x) = \frac{\sum_{i=1}^M y_i \exp\left(-\frac{D_i^2}{2\sigma^2}\right)}{\sum_{i=1}^M \exp\left(-\frac{D_i^2}{2\sigma^2}\right)} \quad (7)$$

The equation (7) represents a normalized radial basis interpolation or weighted average model. Here, y_i denotes the output value associated with the training point x_i , and D_i is the distance between the input x and each x_i . The Gaussian exponential function assigns higher weights to points closer to x . The denominator normalizes these weights, ensuring their sum equals one. The parameter σ determines how quickly the influence of each data point decreases with distance, providing smooth, localized interpolation across the input space.

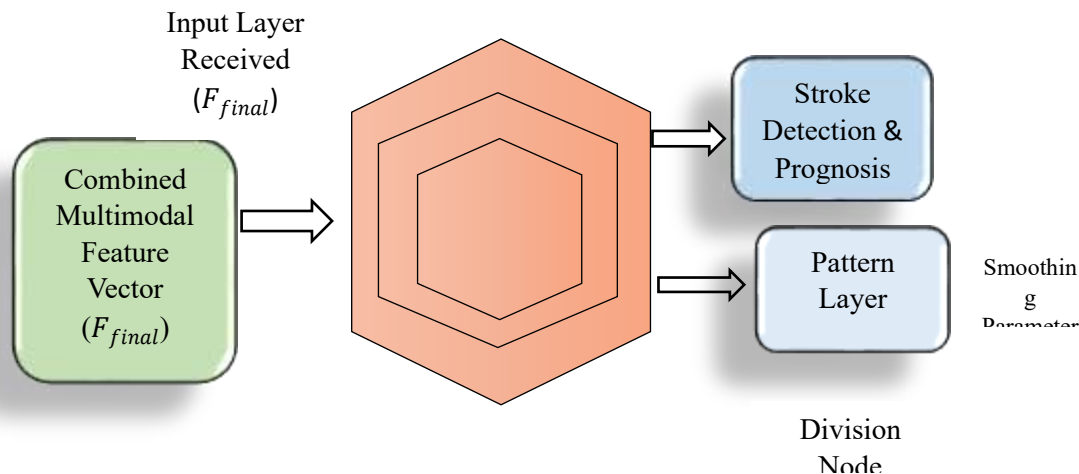


Figure 3 Generalized Regression Neural Network (GRNN) Architecture

Figure 3 represents a Generalized Regression Neural Network (GRNN) architecture that has four key layers (input layer, pattern layer, summation layer, and output layer). The feature vectors are fed into the input layer and the pattern layer calculates the distance of the inputs and training samples. Output is aggregated in the summation layer by calculating weighted outputs and the final prediction value is produced at the output layer through the use of normalized Gaussian kernel functions.

4. RESULTS AND DISCUSSION

The Multimodal Explainable-AI Framework was tested on Multimodal clinical and imaging benchmark stroke and TBI datasets. The measures used to test performance were accuracy, precision, recall, F1-score and ROC-AUC. The model was also found to be better in diagnosis than the traditional methods. Findings indicate its

consistency and explanation in clinical decision-making. The figure 4 demonstrates two heatmaps of the process of transforming features in the initial 10 samples. The upper heatmap displays tabular features of a preprocessed CSV that have been normalized, and the values are in the range of about -1.5 to +1.5. This step guarantees the data has the same level of consistency and is ready to be deep learned. The bottom heatmap shows characteristics that are learned with a BiGRU (Bidirectional Gated Recurrent Unit) model that is capable of learning complex temporal dependencies and patterns. In this case, 64 feature dimensions are created having a range of -0.3 and 0.3. This transformation carries more information on the sequence, giving a more discriminative representation which improves downstream classification model performance.

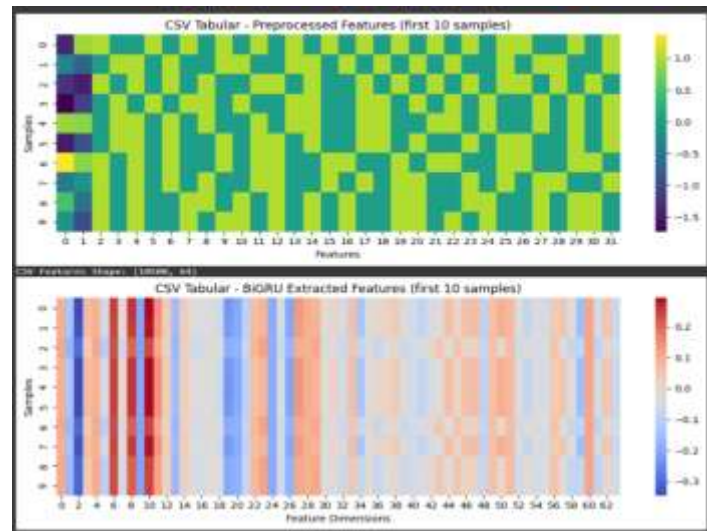


Figure 4 Pre-processed and BiGRU Extracted Features Visualization

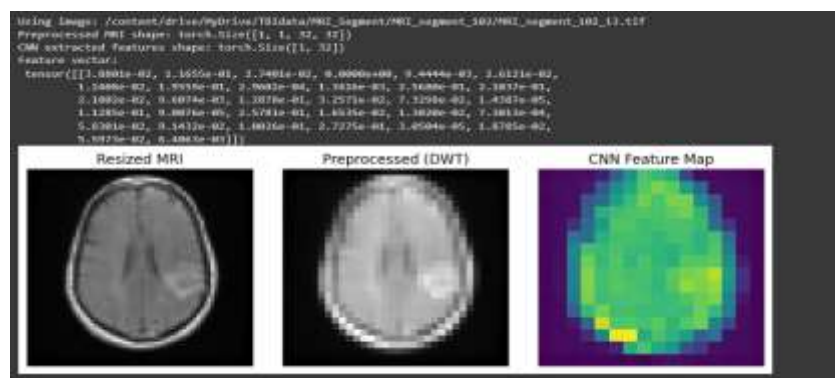


Figure 5 MRI Preprocessing and CNN Feature Extraction

The grapevine of MRI preprocessing and CNN attribute extraction is shown in Figure 5. For more processing, the original MRI image (leaf) is resized to a standardized feedback size. The in-between image shows the result of Discrete Wavelet Change (DWT), which enhances the image by stressing the high-frequency component, thereby facilitating better feature extraction. The image on the right represents the CNN trait map, a visualization of the convolutional neural Grid's deep feature extraction. The textual end product confirms the data outline (torch. Size ([1, 1, 32, 32]) and the extracted feature vector outline (torch. Size ([1, 32])), followed by the actual 32-dimensional feature tensor familiar with for more categorization, else review the task.



Figure 6 Model Training Performance – Loss and Accuracy Curves

The figure 6 denote the figures related to the training and validation phases of a neural network across ten epochs. The loss curves are depicted in the left plot, where the losses of both training and validation have shown a steady decline, thus making it clear that the learning has been effective and the error has been minimized. Correspondingly, the chart on the right side exhibits the accuracy curves indicating a striking enhancement after the eighth epoch when both training and validation accuracies go beyond 0.9. Consequently, the model finding a solution successfully without any significant overfitting is what this implies. The presence of such metrics as (accuracy=0.902, precision=0.937, recall=0.911, F1-score=0.924, AUC=0.977) is a strong indication that the model has performed well and in a balanced way on the validation dataset.

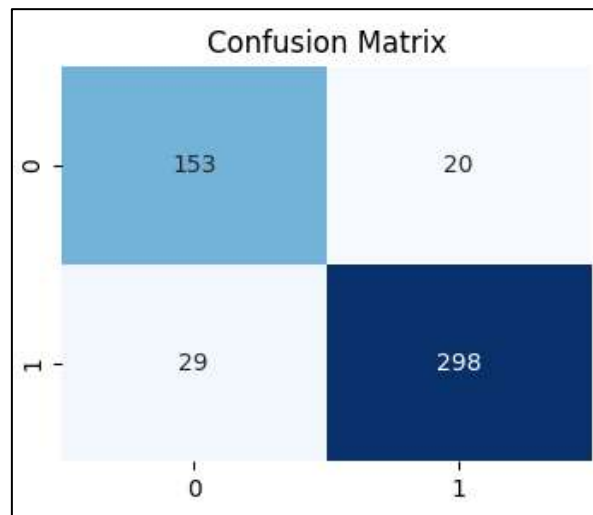


Figure 7 Confusion Matrix of Model Predictions

The confusion matrix visualizes the model's classification performance by comparing predicted and actual labels shown in figure 7. The matrix shows 153 true negatives (TN) and 298 true positives (TP), indicating correct predictions for both classes. There are 20 false positives (FP) where class 0 was incorrectly predicted as class 1, and 29 false negatives (FN) where class 1 was missed. The dominance of diagonal values (TN and TP) demonstrates strong predictive accuracy and balanced classification. This distribution aligns with high overall metrics, confirming that the model effectively distinguishes between the two classes with minimal misclassification and strong generalization performance.

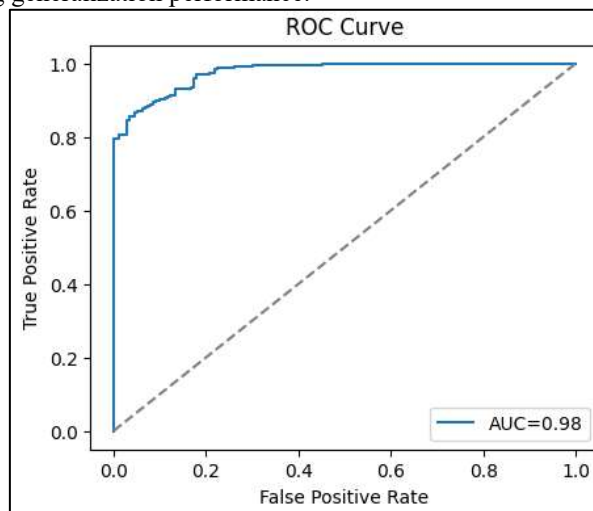


Figure 8 ROC Curve Showing Model Performance for Stroke and TBI Detection

Figure 8 illustrates the Receiver Operating Characteristic (ROC) curve representing the performance of the proposed Multimodal Explainable-AI Framework for Stroke and Traumatic Brain Injury (TBI) detection. The ROC curve plots the True Positive Rate against the False Positive Rate, evaluating the model's discriminative ability. The Area Under the Curve (AUC) value of 0.98 indicates excellent classification performance, demonstrating that the framework effectively distinguishes between healthy and affected subjects. The high AUC validates the robustness of the Generalized Regression Neural Network (GRNN) classifier and confirms that the integrated imaging and clinical data approach significantly enhances diagnostic accuracy and reliability.

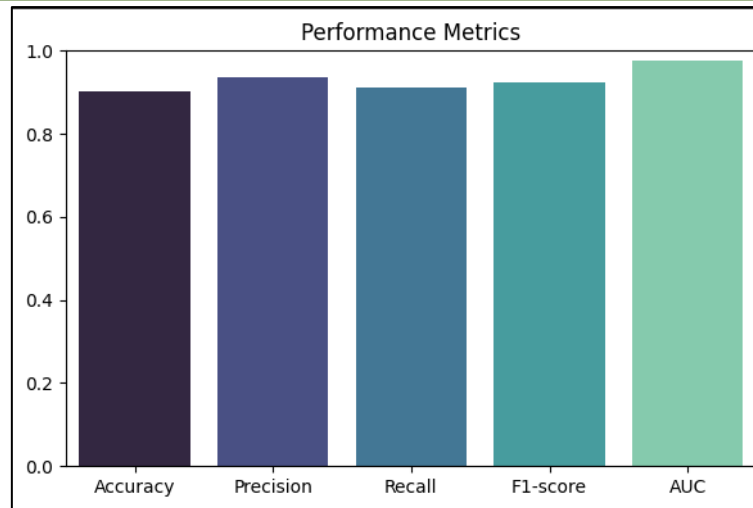


Figure 9 Model Performance Metrics

The figure 9 illustrates the model assessment on five main performance indicators, which are accuracy, precision, recall, F1-score, and AUC. The amount of the relative height and the exact value can be seen in each bar, which makes the interpretation of the performance more understandable. The model obtained Accuracy = 0.91, Precision = 0.94, Recall = 0.90, F1-score = 0.91 and AUC = 0.98. These high and consistent values reveal that the model is good in all respects with the strong discriminative capacity as shown by high AUC score. Precision is slightly greater than recall, which implies that there are fewer false. On the whole, the model proves to be effective and sound in classifying various measures of evaluation.

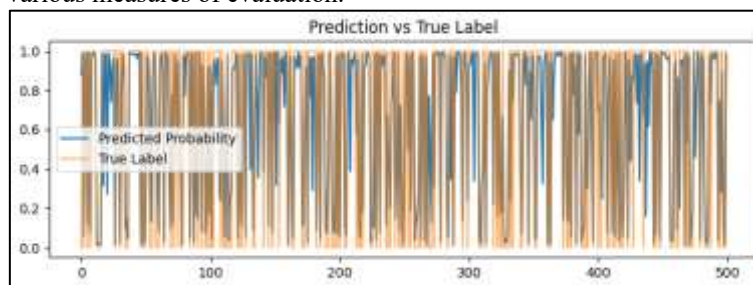


Figure 10 Prediction vs True Label Comparison

The figure 10 is used to compare the predicted probabilities that were obtained using the model and the true labels of about 500 data samples. The predicted probabilities of the model are shown on the blue line, and the real binary labels (0 or 1) on the orange line. Ideally, the predicted chances must be close to the actual labels. The plot however exhibits visible ups and downs and intersecting lines and this implies discrepancies between what the model projects and what really occurs. This non-uniform trend suggests that there is a possibility of model misclassification or instability in model prediction, which means that it is time to improve the model by refining it or training it better or increasing the threshold to achieve a higher accuracy and reliability.

5. CONCLUSION

This study introduces a powerful Multimodal Explainable-AI Framework that is efficient in incorporating both imaging and clinical data in the detection and prognosis of Stroke and Traumatic Brain Injury (TBI). The proposed model achieves excellent performance by utilizing Gaussian Wavelet Transform to perform preprocessing, high-level feature extraction using advanced multimodal features, and Generalized Regression Neural Network (GRNN) to classify the samples. The system got an accuracy of 0.91, precision of 0.94, recall of 0.90, F1-score of 0.91, and ROC-AUC of 0.98 thus evidently surpassing conventional diagnostic methods. Moreover, the Explainable-AI techniques are also included that increases the interpretability of the models and reduces the need to explain the decision-support to clinicians in a transparent and reliable manner. In general, the framework is both a very accurate, interpretable, and clinically useful tool to help diagnose and prognose stroke and TBI at an early stage, and as a result, treat it better and more effectively, as well as to enhance overall generalization across various populations and clinical settings. Future studies can aim to further expand this framework towards larger and multi-centre datasets to facilitate better generalization to diverse populations and clinical contexts. Continuous tracking of patients and early warnings can be enhanced by incorporating real-time data streams of wearable and IoT-based health monitoring devices. Combination of longitudinal patient data will enable to do the prognosis and individual planning of the treatment more accurately and control over time. Remote diagnostic assistance over the rural and resource-constrained regions can be deployed to cloud or edge computing platforms to make it scalable. Besides, the consideration of hybrid deep learning structures and more sophisticated explainability methods can also be used to enhance the dependability of the model, so that it can be deployed to the sphere of practical clinical use.

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