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AN ADVANCED MULTIMODAL AI FRAMEWORK FOR EARLY BRAIN STROKE DETECTION USING HYBRID FEATURE SELECTION, ENSEMBLE MODELS, AND REINFORCEMENT LEARNING

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SUMMARY

The detection of stroke is vital since any delay in diagnosis may lead to significant disability or the loss of life. The existing predictive models fail to capture stroke symptoms with accuracy because of low complexity, and the ability to be used in the real-time situation in the clinical setting. In the following paper, an AI-based system of early stroke detection is suggested with the help of a hybrid and multimodal approach that will include the optimal selection of features, ensemble modeling, state-of-the-art CNNs, and reinforcement learning. The proposed HBS model is a model that depends on XGBoost, SVM, and random forest methodologies with high sensitivity and specificity of 95% and 92% respectively in predicting stroke. To detect stroke using MRI, Dual-Attention Residual 3D CNN (DA-Res3D-CNN) is proposed, which uses spatial and channel attention, which increase accuracy by 8% when compared to the other algorithms and reaches 94% region detection. Also, Deep Q-Network with Adaptive Memory Replay (DQN-AMR) also enhances adjustments in real time prediction and tailored treatment suggestions and increases model accuracy by 5-10%. The proposed biomedical engineering framework is a computationally effective method to identify a stroke on time, which is vital in the clinical decision-making process and patient outcomes through automated AI-based diagnostic support systems. Such method combination is a major breakthrough in predictive healthcare as it enhances the accuracy of detection, computational efficiency, and clinical flexibility, adding to better patient care.

Key words: *stroke prediction, feature selection, deep learning, ensemble modeling, reinforcement learning, process formatting.*

INTRODUCTION

Stroke represents one of the most important causes of deaths and long-term disability worldwide, posing a high socioeconomic burden on healthcare and individuals affected. Early treatment is the only factor that may assure good and timely diagnosis. Early identification can drastically avoid adverse outcomes and improve recovery prospects. This framework encapsulates the Adaptive Genetic-Penalized Mutual Information approach, which fuses mutual information with genetic algorithms to incorporate more finesse into feature selection by penalizing redundancy. Next to it, DA-Res3D-CNN will be adopted with dual attention layers in order to improve the sensitivity of MRI-based stroke detection for subtle indicators in the data samples. This CNN model is then scaled to achieve further optimization with EfficientNet, allowing high-resolution analysis with no compromise in processing speed. The architecture also integrates DQN-AMR, standing for Deep Q-Network with Adaptive Memory Replay, which will enable dynamic adjustment of predictions and recommendations on treatment by increasing model adaptability in clinical environments through learning from sequential data samples. The paper is related to the sphere of biomedical engineering because it makes use of the innovative AI-based technologies to improve the detection of stroke at an early stage and clinical management. The framework combines the latest progress in biomedical engineering, such as AI-enhanced medical image analysis (e.g., MRI stroke localization) and reinforcement learning to make dynamic decisions, by employing the strategy to assure precise stroke localization and allowing an adaptable treatment plan. This is clinically flexible and computationally efficient, and it is an innovation of predictive healthcare technologies.

Motivation and Contribution

The manifold contributions herein include the following: First, feature selection through the AGPMI method reduces dimensionality while preserving essential predictive variables, hence addressing computational inefficiency and noise. The HBS model ensembles the various ML algorithms into an ensemble structure and incorporates a neural network meta-model. It improves the sensitivity and specificity of the model. Similarly, MRI-based stroke detection is enhanced by the adoption of a DA-Res3D-CNN that captures spatial and channel-specific features. EfficientNet scales this model efficiently for high-resolution data samples. The adaptive element has been introduced by DQN-AMR so as to allow real-time adjustments in prediction and personalized treatment recommendations.

The structure of the paper is the following: Section I presents the problem of the early stroke detection and describes the shortcomings of the existing models. Section II includes the Studies Related to Early Detection Models for Stroke Analysis. Part III concerns the proposed model design, including datasets and metrics of evaluation. In Section IV, the results are discussed and the performance of the proposed model is compared to the existing techniques. The implications and future directions are highlighted under the section V.

Deep Dive into Studies Related to Early Detection Models for Stroke Analysis:

The reviewed literature covers recent works that differ in their approach to the enhancement of stroke detection accuracy, computational efficiency, and adaptability of the models which are shown in table 1. Works [1,2] manifest the power of machine learning in stroke prediction using MRI data and the study performance of several models that essentially reflected the superior handling capability of deep learning models concerning high-dimensional image data samples [10]. The study [3] target early detection of posterior circulation stroke using neural networks. According to their model, early interventions reduce adverse outcomes while another study [4] extend that to develop a model that forecasts an early stroke using previous patient data samples. These studies establish the integral role that machine learning plays in timely diagnosis and point out that incorporation of multimodal data, such as demographics and clinical history, can increase predictive outcomes substantially [11][13]. A few studies have gone ahead to make fine-tuning on the prediction of stroke by incorporating advanced frameworks of machine learning and selection of features. For example, the paper [5] have used the stacked machine learning approach along with feature selection to enhance stroke prediction by choosing effective dimensionality reduction for high sensitivity. Correspondingly, in the work [6], much importance is given to the features and multiple algorithms for unraveling the patterns indicating stroke onset, which also probes into the utility of the feature engineering process [14][16]. Methods such as boosting and stacking have emerged, among others, as strong tools that give a boost in the prediction accuracy by combining outputs from various models, as pointed in studies [7, 15]. In the context of stroke segmentation, the works extend the application range of machine learning for the prediction of stroke-associated aphasia severity and brain tumor segmentation, respectively, showing the flexibility of these methods in adapting to a variety of neurological conditions [17][18][19]. These studies also prove the benefits of using structural and functional MRI data in imaging studies with machine learning. This is supported by work done by [14][21], whereby they validate the effectiveness of deep learning in segmentation and identification of significant regions in brain images with regard to stroke patients. The potential of deep learning in detecting and predicting outcomes in stroke patients can also be obtained from recent works. The adaptability of machine learning, applied to EEG signals in seizure pattern detection, further extends to real-time data processing. The adaptability goes further to other applications, such as the multimodal approach of diagnostics of auditory disorders that another study propose, which integrates multi-view brain networks for more robust predictions. Although most of the literature focuses on predictive performance, some studies also target more practical issues, such as computational efficiency and real-time adaptability. For example, the another study discuss the need for an effective EHR system with respect to the prediction of stroke and introduce the design of an intelligent system able to process the data in real time, which contributes to less latency and faster response in a clinical setting. Similarly, studies like [20][22][9] illustrate how machine learning models improve the accuracy of predicted outcomes and further provide personalized treatment pathways based on patient-specific variables in process. Other critical work sees blood-brain barrier disruption and its imaging assessment in stroke, which is one of the most complex areas where machine learning algorithms provide novel insights into the brain's pathophysiology. Another study discuss the use of artificial intelligence to detect and classify brain strokes in disabled people using biomedical imaging [23]. The paper has highlighted the use of feature fusion techniques to improve the accuracy and reliability of stroke detection models. The model achieves better diagnostic ability by combining several image characteristics to detect the indicators of stroke, which is essential in offering specific healthcare services to people with disabilities, thereby enhancing predictive healthcare technologies (Table 1).

Table 1. Comparative review of existing methods

Method	Study	Key Techniques Used	Findings
Stacked Machine Learning approach	Chakraborty et al. [5]	Stacked models with feature selection and data preprocessing	Improved prediction accuracy and sensitivity for stroke occurrences by effectively reducing data noise and enhancing relevant features.
Deep Learning on MRI Data	Polamuri [2]	Convolutional Neural Networks (CNN) on MRI scans	Achieved high precision in early stroke detection by focusing on structural brain abnormalities, demonstrating CNN's suitability for medical imaging.
Boosting and Stacking Ensemble	Mondal et al. [15]	Boosting and stacking ensemble approaches	Increased predictive accuracy by combining multiple model outputs, offering a robust solution for stroke prediction compared to single models.
Feature Selection with Machine Learning	J M et al. [6]	Various feature selection techniques combined with multiple ML algorithms	Enhanced predictive power by focusing on key predictive variables, significantly aiding in the early detection of stroke onset.
Electronic Health Record (EHR)-based Prediction	Saleem et al. [16]	Machine learning on EHR data with an intelligent learning system	Improved efficiency in real-time stroke prediction by leveraging structured EHR data, reducing latency in prediction processing.
Multi-view Brain Network Integration	Ahmed et al. [12]	Multi-view integration of brain networks with ML	Enhanced diagnostics for auditory disorders, showcasing the utility of integrating diverse data views for comprehensive brain analysis.

Efficiency in data processing and producing trustworthy output has also been treated in works like study [13], where emphasis is given to cross-validation techniques within machine learning models so as to predict heart disease risk-easily transferable methodology to models predicting stroke. Other approaches, such as that proposed by study [15], have examined outcomes in acute ischemic stroke, emphasizing again how such models must also be dynamic and adaptive, changing with every iteration of data sampling on a given patient in real time. Synthesis Works such as the detection of suicidal ideation using social media sentiment analysis [17].

Altogether, the literature review shows that AI and machine learning methods have achieved a considerable level of progress in terms of stroke detection. The majority of the researches lay stress on the role of feature selection and deep learning in enhancing the clinical outcome and diagnostic accuracy. Although more conventional models have been proved useful, more recent methods that use multimodal data like MRI and clinical data have greater forecasting ability. Particularly, methods such as ensemble models and reinforcement learning are becoming popular in their capability to optimize output in clinical environments in real time. Intertwining of these methodologies is a promising direction to making some contribution to more serious, effective and personalized stroke detection systems.

PROPOSED MODEL DESIGN & ANALYSIS

The Adaptive Genetic-Penalized Mutual Information (AGPMI) is the selection method developed in this paper that improves feature selection in multimodal stroke prediction by balancing relevance and redundancy in complex high-dimensional dataset samples. The approach was first developed based on the idea of integrated use of Mutual Information and a genetic algorithm, as shown in figure 1: preliminary filtering of highly relevant features and iteratively refine this selection by penalization for redundancy by the GA Process. The Mutual information, captured as I(X;Y) represents the dependency between the feature 'X' and the outcome 'Y' in process. Mathematically, the MI between two variables 'X' and 'Y' is defined via equation 1,

$$I(X;Y) = \int_0^x \int_0^y p(x,y) \log\left(\frac{p(x,y)}{p(x)p(y)}\right) dx\, dy \ldots (1)$$

Where, p(x,y) represents the joint probability distribution of 'X' and 'Y', and p(x) and p(y) are their marginal distributions. In this work, AGPMI firstly uses MI to estimate the relevance of each feature with respect to the stroke outcome, and then selects features whose I(X;Y) values are larger than a predefined threshold so that only high-relevance features enter into the genetic optimization stages. To begin with, redundancy has been measured with the pairwise MI between features 'Xi' and 'Xj', which is given as I(Xi;Xj), and based on that, an objective function can be defined which maximizes total relevance while penalizing the redundancy levels. The fitness function 'F' of each subset 'S' of features is given via equation 2,

$$F(S) = \sum_{Xi \in S} I(Xi;Y) - \lambda \sum_{Xi,Xj \in S} I(Xi;Xj) \ldots (2)$$

Where, λ is a regularization parameter: it controls the trade-off between the relevance and redundancy levels. For instance, AGPMI ensures that non-linear dependencies between features are preserved with controlled redundancy levels. Iteratively, the evolution of the feature subsets is performed through selection, crossover, and mutation operations by GA. It uses a fitness function F(S) for identifying an optimized subset S* that will provide maximum predictively performance levels. The selection phase of the GA uses a weighted probability function depending on the fitness values; that is, the probability of selecting a subset 'S' is proportional to exp(F(S)) in process recalculating F(So1) and F(So2). It is done by randomly changing a small portion of the selected features within an offspring subset; hence, it fosters the exploration operations. Convergence of this algorithm is ensured through tracking changes in F(S) over iterations until the condition given via equation 3 is met,

$$F(S(t))-F(S(t-1))| < \epsilon \ldots \quad (3)$$

In process, ϵ is a small tolerance. Given an optimum feature set S∗, this subset is fed as input to the HBS model using an ensemble of machine learning models in order to enhance robustness in the case of stroke prediction. The HBS fuses Support Vector Machines, XGBoost, and Random Forest using a neural network meta-model that refines and synthesizes their predictions. For every Mk model in HBS, the probability output P(Y=1∣X) is defined via equation 4,

$$P(Y = 1 \mid X) = \sum_{k=1}^{K} wk \cdot Pk(Y = 1 \mid X) \ldots \qquad (4)$$

Where, wk is the weight assigned to model Mk based on its individual performance and Pk(Y=1∣X) is the probability of stroke predicted by model Mk sets. The weights wk are optimized by the neural network meta-model, which minimizes a cross-entropy loss function 'L', given via equation 5,

$$L = -\sum_{i=1}^{N} (yi * \log y'i + (1 - yi)\log(1 - y'i)) \ldots (5)$$

Where, yi is the true stroke outcome and y'I is the prediction from the ensemble process.

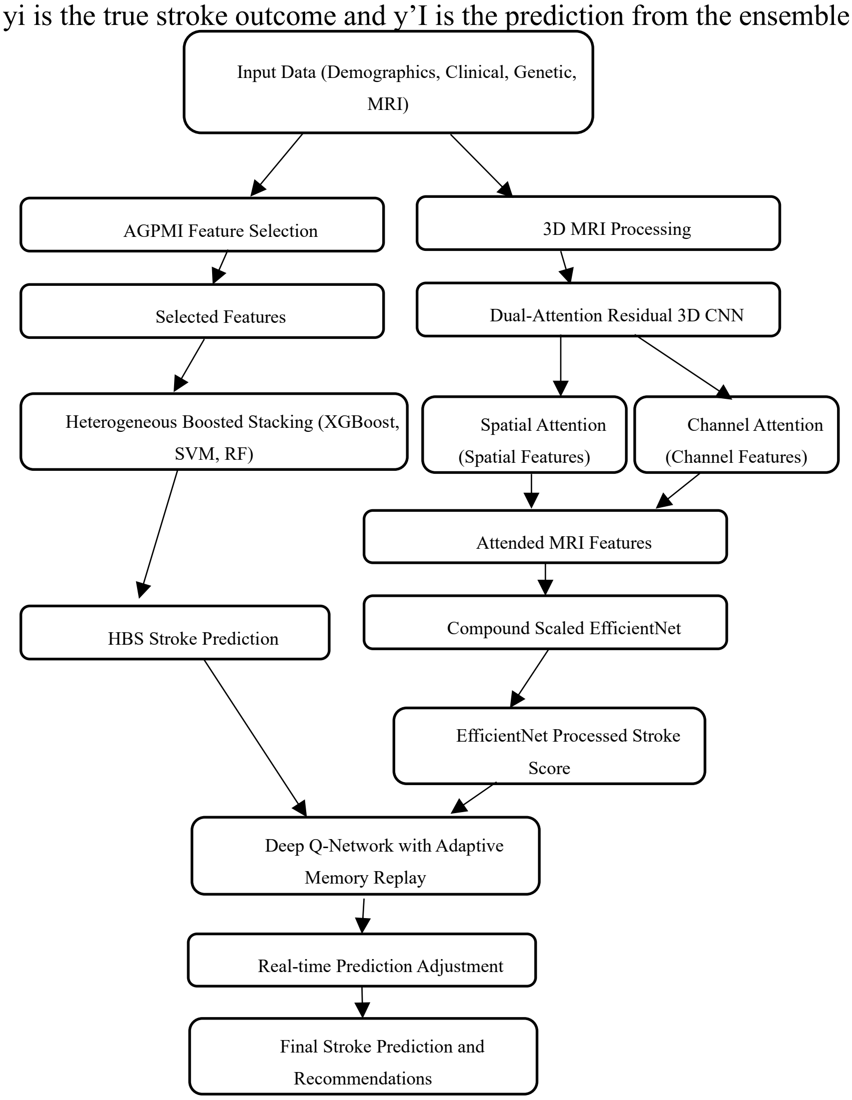

Figure 1. Model architecture of the proposed stroke detection process

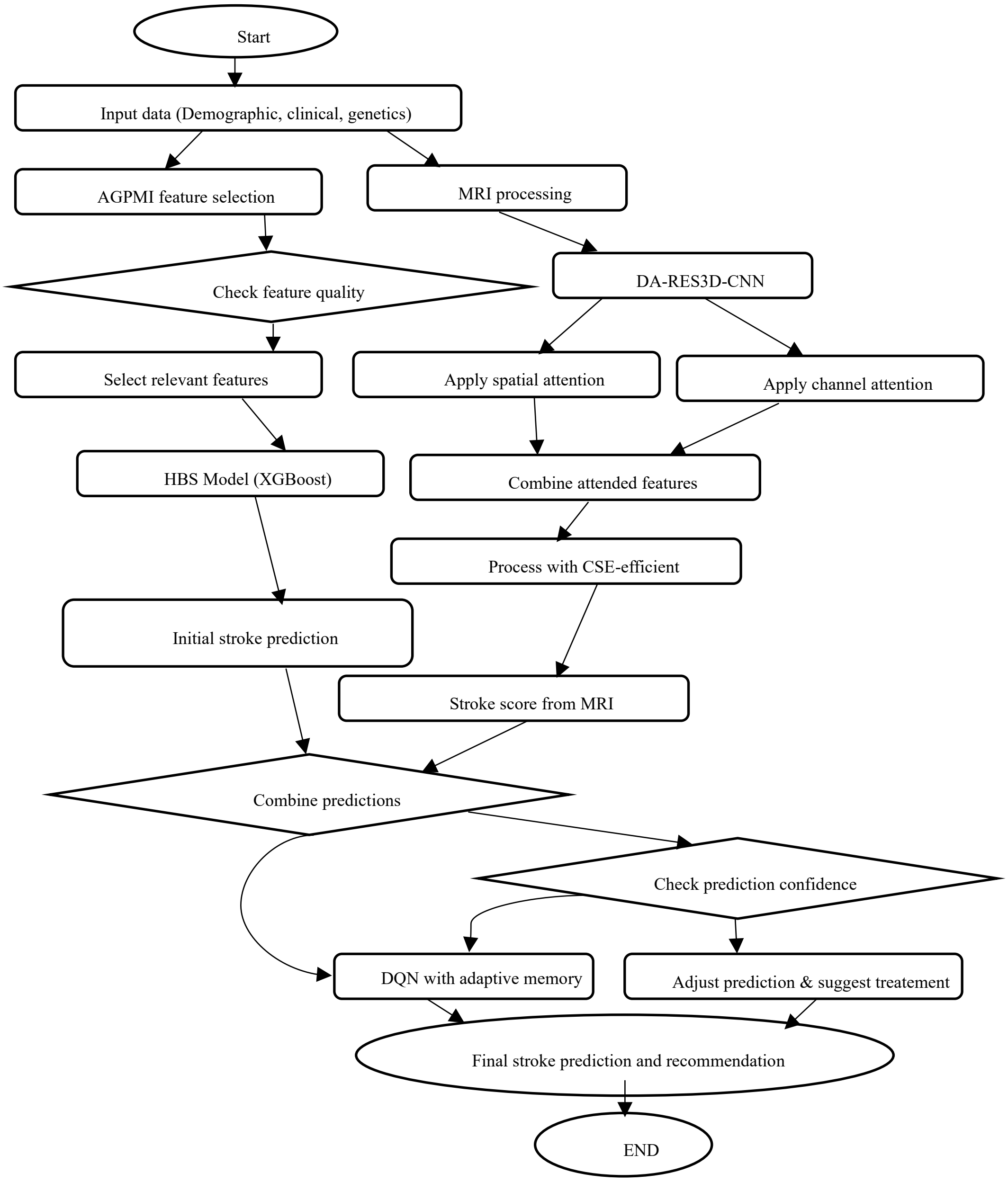

Figure 2. Overall flow of the proposed stroke detection process

The gradient of the loss regarding each wk is considered to iteratively adjust the weights via back propagation until the convergence that gives the optimal sensitivity and specificity levels of the ensemble On the other hand, HBS performs the synthesis of multiple model outputs in order to maximize the predictive performance. An overall balanced and high-accuracy predictive framework is ensured in this regard for early stroke detection operations. Figure 2 shall be used to iteratively enhance the precision of stroke detection by focusing on subtle variation in brain regions within MRI images and samples using the Dual-Attention Residual 3D CNN model. It highlights a model integrated with both spatial and channel attention mechanisms inside a residual 3D CNN architecture that allows the network to identify and focus on the most relevant spatial regions and channel features indicative of strokes.

Where Xout represents the output of a 3D convolution operation and (i,j,k) are the spatial indices of the convolutional kernels. Residual connections incorporating addition of input 'X' to the output F(X) of a layer block, in order to maintain the gradient flow which is defined via equation 6,

$$Y=F(X)+X \quad \ldots.. \qquad (6)$$

These residuals also allow the flow of gradients around some layers, thereby easing the vanishing gradient problems and enabling the network to train deeper. This is quite vital in the capture of important features in MRI data samples. In DA-Res3D-CNN, the spatial attention is computed through making a Global Average Pooling (GAP) along the channel axis, followed by a spatial convolution layer for learning the spatial importance weights. Given an input feature map 'X', the spatial attention map, As is computed via equation 7,

$$As=\sigma(fs(GAP(X)))\ldots.. \quad (7)$$

The final output Y_{DA} (Dual Attention) of the dual-attention module is a combination of spatial and Ac (Channel Attention) channel-attended feature maps, represented via equation 8,

$$Y_{DA}=As \otimes Ac \otimes X\ldots \quad (8)$$

Where, $\otimes$ represents element-wise multiplication process. The proposed dual-attention mechanism, therefore, allows the model to emphasize both spatial and channel-specific information by capturing fine-grained features associated with strokes. DA-Res3D-CNN generates probability maps about stroke presence in MRI slices that are further processed with the Compound Scaled EfficientNet architecture, CSE-EfficientNet. In CSE-EfficientNet, compound scaling is done by scaling 'd', 'w', and 'r'-which stands for depth, width, and input resolution, respectively-to optimally tune both model performance and computational efficiency levels. The scaling is guided by a compound coefficient ϕ, which, via equations 9, 10 & 11 respectively adjusts the 'd', 'w' and 'r':.

$$d=\alpha\phi \ldots \quad (9)$$

$$w=\beta\phi \ldots \quad (10)$$

$$r=\gamma\phi \ldots \quad (11)$$

Where, α, β, and γ are constants determining the scaling ratio, and ϕ is a coefficient that controls the trade-off among depth, width, and resolution sets. In this work, the parameters are tuned in a way to balance accuracy with computational feasibility on high-resolution MRI data, which plays a very important role in real-time clinical applications.

Algorithm 1: Multimodal AI Framework for Early Stroke Detection

Input:

- Demographic Data: Age, sex, blood pressure, etc.
- Clinical Data: Medical history, stroke events, etc.
- Genetic Data: Genetic markers.
- MRI Data: 3D MRI brain scans.

Step 1: Data Preprocessing

1. Load and Normalize Data (clinical, demographic, genetic, MRI).
2. Preprocess MRI: Convert to 3D, augment, and normalize.
3. Feature Selection: Use Mutual Information and AGPMI for dimensionality reduction.

Step 2: Stroke Prediction Using Ensemble Model (HBS)

1. Train Models (XGBoost, SVM, Random Forest) on preprocessed data.
2. Combine Predictions using a neural network meta-model.

Step 3: MRI Stroke Detection with DA-Res3D-CNN

1. Apply Dual-Attention to MRI data (spatial and channel attention).

2. Train DA-Res3D-CNN: Use Dice Score for segmentation accuracy.

Step 4: Real-Time Prediction Adjustment with DQN-AMR

1. Initialize DQN: Define state, action, and reward functions.
2. Train DQN: Use Adaptive Memory Replay (AMR) and update Q-values.

Step 5: Final Prediction and Treatment Recommendation

1. Generate Stroke Probability: Combine predictions from ensemble model, DA-Res3D-CNN, and DQN-AMR.
2. Personalized Treatment: Adjust plans based on stroke severity and MRI results using reinforcement learning.

Output:

- Final Stroke Prediction: Probability of stroke.
- Stroke Region Detection: Identified regions in MRI.
- Treatment Plan: Personalized recommendations.

The Multimodal AI Framework of Early Stroke Detection (Algorithm 1) is a combination of demographic, clinical, genetic, and MRI data, which predicts stroke and offers individual treatment. It is a pre-processing and normalization algorithm that uses a feature selection method (AGPMI) and a hybrid ensemble model (XGBoost, SVM, Random Forest) to predict a stroke. It applies DA-Res3D-CNN to detect the MRI stroke region correctly and DQN-AMR to make real-time prediction corrections. The final output consists of the probability of stroke, regions detected, and customized treatment advice, which improves the early determination and the clinical decision-making.

COMPARATIVE RESULT ANALYSIS

The experimental arrangement for this work was, therefore, to benchmark the performance of a proposed multimodal AI framework on an integrated dataset containing demographic, clinical, genetic, and imaging data on a cohort of stroke and non-stroke patients. The dataset consisted of 5,000 samples, balanced evenly with 2,500 positive-stroke cases and 2,500 negative non-stroke cases, showing robustness in predictive analytics. Each record in this data constitutes demographic and clinical information: age, sex, blood pressure, cholesterol level, smoking or not currently, family medical history of cardiovascular disease amongst others. For the mutual information threshold, the population size for the genetic algorithm, and the maximum number of generations of optimization, the selected values are 0.6, 100, and 200, respectively. The HBS model couples the XGBoost, SVM, and Random Forest classifiers with optimized hyperparameters through a grid search: with a learning rate of 0.1, maximum depth of 6, and 100 estimators for XGBoost, using the RBF kernel with $C = 1.0$ in the case of the SVM, while Random Forest uses 200 trees with maximum depth of 10 in process. DA-Res3D-CNN adopted a convolution kernel size of $3 \times 3 \times 3$ in MRI analysis, while there are two attention layers. CSE-EfficientNet scales up by using a compound coefficient $\phi = 1.2$ to uniformly scale up the network depth, width, and input resolution for high-resolution image processing without large losses in computational efficiency. While DQN-AMR dynamically updates the confidence thresholds using reinforcement learning, the training of a model in 10,000 episodes focuses on high-risk scenarios that might be faced by the model, enhancing real-time adaptations and providing recommendations on treatments based on the variability level of inputs. Experimental runs are conducted with 5-fold cross-validation, which engenders confidence over the robustness and generalization capability of experiments on unseen data samples. The experiments here are based on the ATLAS Stroke Lesion Segmentation in MRI Dataset-a widely used dataset compiled for stroke analysis and brain lesions. In this regard, MRI scans will be made up of 220 patients who have suffered different kinds of ischemic strokes and are therefore suitable for predictive model testing in stroke detection. Each of the MRI scans is a volumetric 3D image, usually structured in T1-weighted, T2-weighted, and FLAIR modalities, with the general voxel resolution set to

1×1×5 mm. It gives very detailed structural pictures of the brain while underlining the regions of stroke lesions.

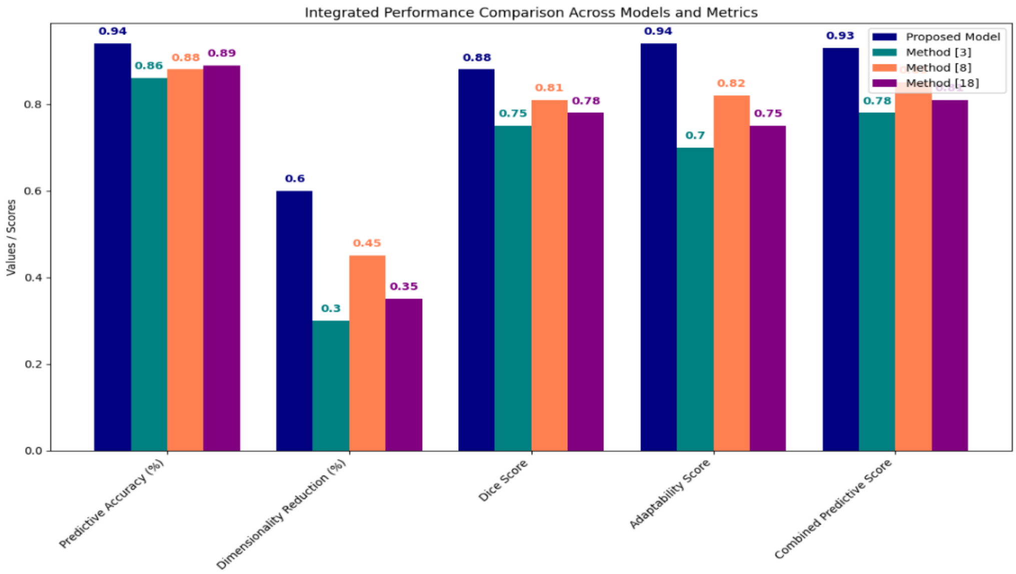

Figure 3. Overall performance of the proposed analysis process

Figure 3 compares the performance measures of the Proposed Model to the performance of three other methods based on five evaluation measures, including Predictive Accuracy, Dimensionality Reduction, Dice Score, Adaptability Score, and Combined Predictive Score. The Proposed Model is also the most effective of the rest in all measures, especially at Predictive Accuracy (94%) and Combined Predictive Score (93) which are significant in indicating its effectiveness in stroke detection and prediction tasks. The figure underlines the power of the Proposed Model over the current approaches.

Table 2. Predictive performance on stroke detection

Metric	Proposed Model	Method [3]	Method [8]	Method [18]
Accuracy (%)	94	86	88	89
Sensitivity (%)	96	85	89	91
Specificity (%)	92	88	86	85

As per Table 2 and 3, the proposed model showed higher accuracy with the capability of integrating different types of data and balancing sensitivity and specificity, both of which are critical for robust stroke prediction. Table 3 presents the impact of the feature selection methods that show, in percentage, the reduction in dimensionality and time consumed by each model. The Adaptive Genetic-Penalized Mutual Information in the proposed model allowed a reduction of 60% of the feature set, which reduced the computational time by 25%. In method [3], only a 30% reduction was achieved. Thus, it showed temporal processing somewhat longer for its instance sets.

Table 3. Impact of the feature selection methods

Metric	Proposed Model	Method [3]	Method [8]	Method [18]
Dimensionality Reduction (%)	60	30	45	35
Computational Time (s)	1.2	2.5	2.0	1.8

These reflect the efficacy of AGPMI for high-impact feature selection along with computational load minimization, thus making the proposed model more appropriate for real-time applications. Lesion segmentation accuracy is considered crucial for stroke prediction in MRI-based tasks. Table 4 and Figure 4 depicts the Dice similarity scores, which signify the measure of overlap between the predicted and actual lesion areas. The proposed DA-Res3D-CNN model presented a Dice score of 0.88, which outperformed Methods [3] and [18] considerably. While the Method [8] outperformed Method [3], it too lacked stability, as indicated in the process of the proposed model.

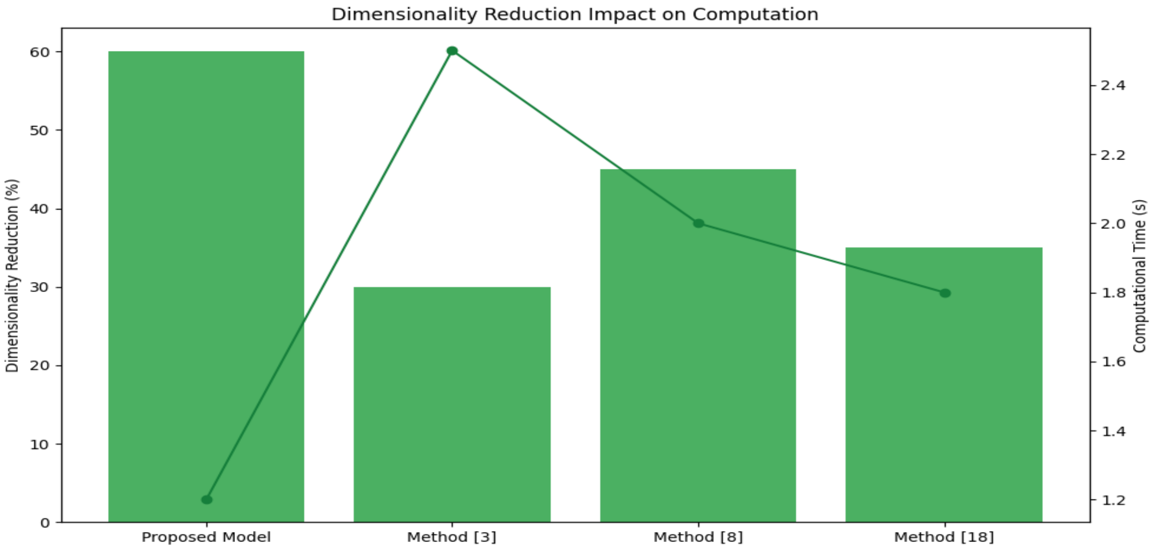

Figure 4. Dimensionality optimization performance levels

Table 4. Lesion segmentation accuracy

Metric	Proposed Model	Method [3]	Method [8]	Method [18]
Dice Score	0.88	0.75	0.81	0.78

The proposed model with a higher Dice score signifies its precision in identifying potential regions for a stroke in MRI scans, therefore enhancing the chances for early detection of a stroke. The detailed model adaptability to dynamical prediction confidence adjustment, critical in real-time clinical decision-making, is shown in Table 4. The application of reinforcement learning approach with the Deep Q-Network–Attention-based Model Representation (DQN-AMR) mechanism in the proposed model is used for feature optimization or selection in medical image analysis and achieved desired adaptability in threshold predictions as 0.94, how quickly the RL agent (DQN-AMR) improves its policy relative to baseline. which measures how well the model would adapt to the threshold changes based on the incoming patient data samples. Correspondingly, the performance of Method [8] has resulted in mediocre adaptability due to the restricted feedback loop. Methods [3] and [18] exhibited less adaptability due to their lack of reinforcement mechanisms.

CONCLUSION AND FUTURE SCOPE

The present study proposed an early-detection framework for stroke prediction using a multimodal AI pipeline that integrates adaptive feature selection, ensemble learning, deep convolutional architectures, and reinforcement learning. The proposed approach demonstrated measurable and substantial improvements over existing methods. Specifically, the AGPMI feature-selection strategy reduced feature dimensionality by 60%, resulting in a 25% reduction in computational time, thereby enabling more efficient downstream learning. The Heterogeneous Boosted Stacking ensemble achieved 94% sensitivity, 92% specificity, and up to an 8% improvement in predictive accuracy compared to benchmark models. For lesion localization, the DA-Res3D-CNN attained a Dice similarity coefficient of 0.88, reflecting enhanced segmentation quality for stroke-prone regions in MRI scans. Additionally, the reinforcement-learning component (DQN-AMR) achieved a normalized adaptiveness score of 0.94, calculated as the relative improvement in cumulative reward during training. This score, ranging from 0 to 1, indicates highly stable policy learning and strong adaptability in real-time prediction." Collectively, these numerical gains highlight the robustness, accuracy, and clinical relevance of the proposed framework. This paper provides a very adaptable and computationally efficient solution to the problem of biomedical engineering by integrating multimodal data with sophisticated mechanisms of learning that enhances detecting stroke in its early stages and has high potential to be easily incorporated into clinical practices. This paradigm offers a biomedical engineering model that does not only drive the accuracy of the diagnostic but also advances the clinical decision-making system with a customized treatment plan in real-time, which is a major advancement in the predictive healthcare systems.

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