

Brain Stroke Prediction Using MRI Images Based on Hybrid CNN–GRU Deep Learning Model

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Abstract: Brain stroke is a severe neurological disorder that may cause permanent disability or death if not diagnosed at an early stage. Accurate interpretation of brain Magnetic Resonance Imaging (MRI) scans is challenging due to the complex spatial patterns and sequential relationships between slices. Traditional machine learning approaches rely on handcrafted features and often fail to capture deep spatial and temporal characteristics of MRI data. To address this limitation, this study proposes a hybrid deep learning framework that integrates Convolutional Neural Networks (CNN) and Gated Recurrent Units (GRU) for automated stroke prediction. CNN is utilized to extract spatial features such as lesion patterns and structural abnormalities from individual MRI slices, while GRU captures temporal dependencies across consecutive slices. The combined CNN–GRU architecture enhances feature representation and improves classification performance. Experimental evaluation demonstrates that the proposed model effectively distinguishes stroke-affected cases from normal MRI scans with improved accuracy, precision, recall, and F1-score. The system provides a reliable computer-aided diagnostic tool that can support clinicians in early stroke detection and timely medical intervention.

Index terms - Brain Stroke Detection, Magnetic Resonance Imaging (MRI), Deep Learning, Convolutional Neural Network (CNN), Gated Recurrent Unit (GRU), Medical Image Analysis, Stroke Prediction, Hybrid CNN–GRU Model.

1. INTRODUCTION

Brain stroke, also known as Cerebrovascular Accident (CVA), is one of the leading causes of death and long-term disability worldwide. It occurs when the blood supply to a part of the brain is interrupted or reduced, preventing brain tissues from receiving oxygen and nutrients. Early diagnosis of stroke is critical because delayed treatment can lead to severe neurological damage or even death. Medical imaging techniques such as Magnetic Resonance Imaging (MRI) are widely used for detecting structural abnormalities in brain tissues and identifying stroke-affected regions.

Traditional stroke diagnosis relies on manual interpretation of MRI scans by experienced radiologists. However, analyzing multiple MRI slices is time-consuming and may lead to misinterpretation due to human fatigue or subtle variations in brain structures. Conventional machine learning approaches have been applied to assist diagnosis, but these methods depend on handcrafted feature extraction and often fail to capture complex spatial patterns present in medical images.

Recent advancements in deep learning have significantly improved medical image analysis by automatically learning hierarchical features from large datasets. Convolutional Neural Networks (CNN) are highly effective in extracting spatial features such as textures, edges, and lesion patterns from medical images. However, MRI scans consist of multiple sequential slices, and analyzing each slice independently may ignore important contextual relationships between slices.

To address this limitation, recurrent neural networks such as Gated Recurrent Units (GRU) can be integrated with CNN models to capture sequential dependencies between consecutive MRI slices. In this research, a hybrid CNN–GRU deep learning model is proposed for automated brain stroke prediction using MRI images. The CNN component extracts spatial features from individual MRI slices, while the GRU component models temporal relationships between slices to improve classification accuracy. The proposed system aims to provide an intelligent computer-aided diagnostic tool that assists healthcare professionals in early stroke detection and supports timely medical intervention.

2. LITERATURE SURVEY

1. A Survey on Deep Learning: Algorithms Techniques and Applications

Thanks to deep learning's supremacy, machine learning is poised to enter its heyday. Deep learning uses several levels of data abstraction to build models in computers. Data processing has been transformed via model transfers, generative adversarial networks, and convolutional neural networks. Since it has never been depicted through a multiscope, this lightning-fast field offers a window of opportunity

for learning. These powerful techniques are like mysterious black boxes that will inevitably obstruct progress if they are not understood. Furthermore, deep learning has been misrepresented as the answer to every machine learning problem. Before getting into innovative deep learning applications. Additionally, it explored possible future areas of research in deep learning, such as online learning, unsupervised learning, and black-box models.

2. Segnet: A deep convolutional encoder-decoder architecture for image segmentation

Deep fully convolutional neural networks are used in the novel and useful SegNet architecture for semantic pixel-wise segmentation. VGG16's 13 convolutional layers are topologically equivalent to an encoder network [1]. The decoder network converts feature maps from the encoder into full-resolution input feature maps when it comes time for the pixels to identify themselves. SegNet's decoder upsamples the lower-resolution input feature map using an unusual technique. The decoder performs non-linear upsampling using the pooling indices following the encoder's max-pooling step. This disables upsampling training. Trainable filters are used to convolve sparse upsampled maps to create dense feature maps. DeconvNet [4], FCN [2], and DeepLab-LargeFOV [3] are notable alternatives to this concept. The association between accuracy and memory performance in segmentation is evident by this comparison. Scene comprehension was one of the applications that motivated SegNet. When it comes to inference, its main design objectives are memory and computational efficiency. Compared to previous designs, stochastic gradient descent allows for end-to-end training with a far reduced number of trainable parameters. SegNet and other systems are controlled by SUN RGB-D interior scene segmentation and road scene benchmarking. These quantitative studies show that SegNet outperforms rival designs in terms of inference time and memory efficiency. See a live example of our Caffe SegNet implementation at <http://mi.eng.cam>.

3. Recent progress in semantic image segmentation:

Medical and intelligent transportation use semantic image segmentation, a significant application of computer vision and image processing. Academics often use multiple benchmark datasets to evaluate algorithm performance. Research on semantic segmentation has been ongoing for quite some time. Segmentation has come a long way since the advent of Deep Neural Networks (DNNs). In this research, we categorise semantic image segmentation techniques as either old or modern DNN. We begin with a brief overview of the original method and available datasets for segmentation, and then we dive

deep into eight different areas of recent DNN-based methods: pyramid methods, fully convolutional networks, upsample methods, FCN-CRF methods, dilated convolution, backbone network enhancements, multi-level feature and multi-stage methods. At last, this part comes to a close.

4. Machine learning for brain stroke: a review

Thanks to machine learning (ML), personalized stroke treatment with quick and accurate predictions is now a reality in healthcare settings. Despite the growing use of machine learning and deep learning in healthcare, several crucial research problems are still being ignored. The four functional categories that best characterize the state-of-the-art machine learning approaches for brain stroke are all thoroughly covered in this paper. 39 ML were found to be useful in brain stroke research between 2007 and 2019 in the online scientific database ScienceDirect. Support vector machines (SVMs) yield the best outcomes out of 10 stroke studies. The number of research that concentrate on stroke diagnosis and therapy varies noticeably. Stroke records frequently contain brain imaging scans. Finally, Support Vector Machines and Random Forests are both effective in every situation. ML methods for brain stroke are illustrated in this article.

5. A fast learning algorithm for deep belief nets:

We employ "complementary priors" to lessen the burden of explaining away effects, making inference easier in highly-connected belief networks with several hidden layers. A greedy, quick method employing complementary priors may be used to train a directed belief network one layer at a time if its initial two layers are an undirected associative memory. The rapid, greedy method initiates a slower learning procedure that fine-tunes weights via a contrastive wake-sleep strategy. A three-hidden-layer network can provide a reliable generative model of handwritten digit pictures and label distribution after few adjustments. This generative model outperforms even the most advanced discriminative learning algorithms when it comes to classifying numbers. Substantial ravines reflect the low-dimensional manifolds on which the numbers lie in the top-level associative memory's free-energy landscape. Investigating these ravines and uncovering the memory's goals is made simple via directed linkages.

6. Nidhi Shashikumar (2026) proposed a data-driven framework integrating predictive maintenance and inventory optimization in medical device supply chains. The study employs hybrid machine learning models such as Random Forest, LSTM, and XGBoost to predict equipment failures, while ARIMA is used for demand forecasting. The integration of these models enables proactive maintenance scheduling

and optimized inventory control, reducing equipment downtime, minimizing overstocking and shortages, and improving overall supply chain efficiency. The findings highlight that combining predictive analytics with inventory management enhances operational reliability, reduces costs, and supports better decision-making in healthcare logistics[6].

3. METHODOLOGY

i) Proposed Work:

The suggested approach offers an automated deep learning framework for MRI image-based brain stroke prediction. To increase picture quality and provide consistent input for the model, brain MRI datasets are first gathered and preprocessed using methods including scaling, normalization, noise reduction, and contrast enhancement. To improve dataset variety and avoid overfitting, data augmentation techniques including rotation, flipping, and zooming are used. To properly assess the model's performance, the dataset is split into training and testing sets after preprocessing.

A hybrid CNN-GRU deep learning model forms the basis of the suggested method. From individual MRI slices, the Convolutional Neural Network (CNN) retrieves significant spatial information such as aberrant structures, lesion borders, and tissue patterns. The Gated Recurrent Unit (GRU), which records temporal relationships between successive MRI slices, receives these spatial information. The CNN-GRU model accurately classifies MRI data into stroke or normal categories by using both spatial and sequential information. Performance indicators like acc are used to assess the system.

ii) System Architecture:

The system architecture for brain stroke prediction is designed to process MRI brain images through a sequence of deep learning stages to achieve accurate classification. Initially, MRI brain image datasets are collected and passed through a preprocessing stage where operations such as resizing, normalization, and noise removal are applied to enhance image quality and maintain uniform input size. Data augmentation techniques such as rotation, flipping, and zooming are further applied to increase dataset diversity and improve model generalization. After preprocessing, the dataset is divided into training and testing subsets to train the deep learning model and evaluate its performance. Following preprocessing, the MRI images are processed by a hybrid deep learning architecture consisting of Convolutional Neural Networks (CNN) and Gated Recurrent Units (GRU). The CNN component extracts spatial features from individual MRI slices by identifying patterns such as tissue

structures, lesion boundaries, and abnormal brain regions. These spatial features are then passed to the GRU network, which captures temporal relationships between consecutive MRI slices to understand the progression of stroke-related abnormalities. The combined CNN-GRU architecture integrates spatial and sequential information to perform final classification, determining whether the MRI scan corresponds to a normal brain or a stroke condition. This architecture improves prediction accuracy and supports efficient automated diagnosis.

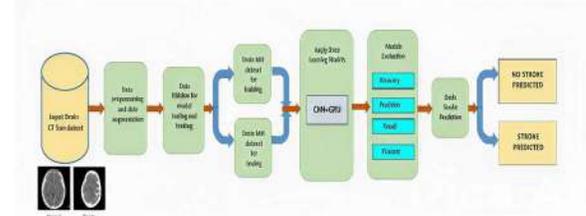


Fig.1. Proposed Architecture

iii) MODULES:

a) Data Collection and Preprocessing Module

The acquisition of MRI brain images and their preparation for model training are handled by this module. To increase picture quality, it incorporates crucial preprocessing techniques such as scaling, normalization, noise reduction, and contrast enhancement. Before being input into the CNN, these procedures guarantee that every MRI slice is standardized. Effective preprocessing minimizes mistakes brought on by inconsistent or poor-quality input data and improves the model's capacity to extract significant features.

b) Image Augmentation Module

This module uses augmentation techniques including rotation, flipping, zooming, shifting, and brightness modification to overcome the problem of little medical datasets. The dataset is made more robust and diversified by producing many versions of each MRI slice. This improves accuracy on unknown MRI images by preventing overfitting and enabling the CNN-GRU model to generalize more effectively.

c) CNN-Based Spatial Feature Extraction Module

This program extracts spatial data from each MRI slice using Convolutional Neural Networks (CNN). It recognizes crucial visual patterns that are necessary for stroke detection, such as tissue structure, lesion borders, and texture alterations. High-level spatial information is captured by the CNN, which transforms each image into a comprehensive feature map. The following step, which examines temporal correlations, uses these extracted characteristics as input.

d) GRU-Based Temporal Feature Learning Module

This module learns temporal connections between successive MRI slices using the Gated Recurrent Unit

(GRU) network once spatial data are retrieved. GRU captures the evolution of stroke-related anomalies by analyzing how the extracted characteristics change from one slice to the next. Because MRI scans are sequences rather than single, independent pictures, this temporal modeling is essential.

e) **CNN-GRU Classification Module**

To categorize MRI data into stroke or normal groups, this module combines temporal and spatial information. By combining the advantages of both algorithms, the CNN-GRU hybrid model creates a prediction system that is more intelligent and accurate. A quick and accurate diagnosis is made possible by the final classification layer's output of the stroke likelihood.

f) **Performance Evaluation Module**

Metrics including accuracy, precision, recall, F1-score, and confusion matrix are used by this module to assess the system. It facilitates comparing the performance of the hybrid model with that of conventional CNN or machine learning techniques. Evaluation guarantees the model's dependability and confirms its efficacy for practical clinical use.

iv) **ALGORITHMS:**

a) **Convolutional Neural Network (CNN)**

The CNN algorithm is used in this project to extract detailed spatial features from individual MRI slices. It learns important visual patterns such as edges, textures, lesions, and tissue abnormalities that indicate the presence of stroke. Through convolution, activation, and pooling layers, CNN captures high-level spatial representations that manual methods or traditional machine learning models often miss. These extracted features form the foundation for understanding visual abnormalities in brain MRI images.

b) **Gated Recurrent Unit (GRU)**

The GRU algorithm is employed to analyze temporal or sequential dependencies across consecutive MRI slices. Unlike CNN, which focuses only on spatial features, GRU captures how stroke-related patterns change from one slice to the next. It uses update and reset gates to efficiently store relevant information while discarding noise, making it faster and more stable compared to LSTM. This ability to learn slice-to-slice progression is essential in medical imaging, where lesions often evolve across multiple frames.

c) **CNN-GRU Hybrid Model**

The hybrid CNN-GRU architecture combines the strengths of both algorithms to create a more intelligent and accurate stroke prediction system. CNN provides rich spatial features for each MRI slice, while GRU processes these features sequentially to understand temporal relationships. This integration enables the system to learn both what

is in the image and how it changes across slices, significantly improving its ability to detect subtle stroke indicators. The hybrid model therefore outperforms standalone CNN or GRU networks.

4. **EXPERIMENTAL RESULTS**

Preprocessed MRI brain image datasets were used to train and evaluate the suggested CNN-GRU hybrid model. The CNN layers retrieved spatial characteristics from individual MRI slices during the training phase, including tissue architecture, lesion borders, and aberrant brain areas. The GRU network then received these extracted properties and used them to learn the temporal correlations between successive slices. In order to increase the dataset's variety and lessen overfitting, data augmentation techniques were used, which allowed the model to perform well when applied to previously unknown MRI pictures.

Standard classification measures including accuracy, precision, recall, and F1-score were used to assess the performance of the suggested model. According to the experimental findings, the CNN-GRU hybrid architecture outperforms standalone CNN and conventional machine learning techniques in terms of prediction accuracy. The model successfully differentiates between normal and stroke-affected MRI data, as shown by the confusion matrix and performance graphs. These findings verify that the suggested approach offers accurate forecasts and can assist medical practitioners in early stroke diagnosis and decision-making.

Accuracy: The ability of a test to differentiate between healthy and sick instances is a measure of its accuracy. Find the proportion of analysed cases with true positives and true negatives to get a sense of the test's accuracy. Based on the calculations:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

$$\text{Accuracy} = \frac{(TN + TP)}{T}$$

Precision: The accuracy rate of a classification or number of positive cases is known as precision. Accuracy is determined by applying the following formula:

$$\text{Precision} = \frac{\text{True positives}}{\text{True positives} + \text{False positives}} = \frac{TP}{TP + FP}$$

$$\text{Precision} = \frac{TP}{(TP + FP)}$$

Recall: The recall of a model is a measure of its capacity to identify all occurrences of a relevant machine learning class. A model's ability to detect class instances is shown by the ratio of correctly predicted positive observations to the total number of positives.

$$Recall = \frac{TP}{(FN + TP)}$$

F1-Score: A high F1 score indicates that a machine learning model is accurate. Improving model accuracy by integrating recall and precision. How often a model gets a dataset prediction right is measured by the accuracy statistic..

$$F1 = 2 \cdot \frac{(Recall \cdot Precision)}{(Recall + Precision)}$$

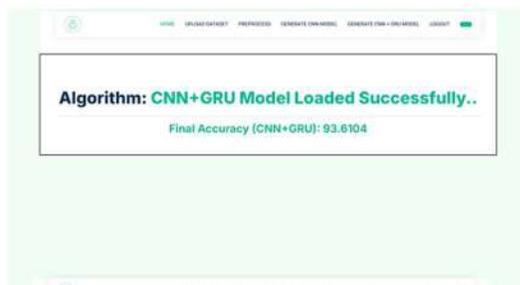


Figure 2: hybrid CNN-GRU model

This figure illustrates the successful loading of the hybrid CNN-GRU model, which combines spatial and sequential learning. The model achieves an improved final accuracy of 93.61%, demonstrating better performance compared to the standalone CNN model.



Fig 3 CNN model used for spatial feature extraction

This figure shows the successful generation of the CNN model used for spatial feature extraction from MRI brain images. The system reports a final classification accuracy of 81.20%, indicating the performance of the standalone CNN model.



Fig 4 image upload interface

This figure presents the image upload interface of the system where users can upload MRI brain images for stroke analysis. The interface allows selecting and uploading MRI scans that will be processed by the trained deep learning model.

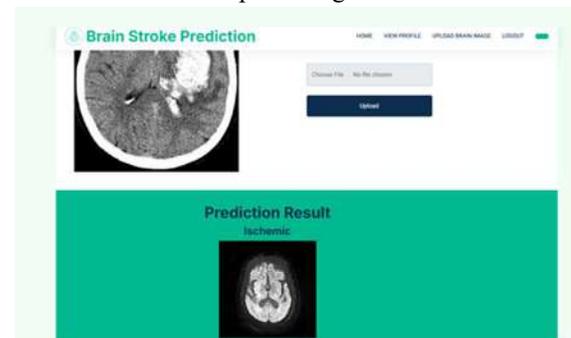


Fig: 5. prediction result interface

This figure displays the prediction result interface of the proposed system. After uploading the MRI image, the CNN-GRU model analyzes the scan and predicts the stroke type, showing the result as Ischemic stroke along with the processed MRI image.

5. CONCLUSION

This research presents an intelligent deep learning-based system for brain stroke prediction using MRI images. The proposed hybrid CNN-GRU model effectively combines spatial feature extraction and sequential learning to analyze complex MRI data. The CNN component captures important visual patterns such as tissue structures and lesion regions, while the GRU model learns dependencies between consecutive MRI slices. This integration enables the system to detect stroke-related abnormalities more accurately than traditional machine learning methods. Experimental results demonstrate that the hybrid CNN-GRU model achieves improved prediction performance, with higher accuracy compared to the

standalone CNN model. The developed system also provides a user-friendly interface that allows uploading MRI images and obtaining automated stroke prediction results. Therefore, the proposed approach can assist healthcare professionals in early stroke diagnosis, reduce manual analysis effort, and support faster clinical decision-making for better patient outcomes.

6. FUTURE SCOPE

The proposed CNN-GRU based brain stroke prediction system can be further improved by using larger and more diverse MRI datasets to enhance the model's generalization and prediction accuracy. Advanced deep learning architectures such as 3D CNNs, attention-based models, or transformer networks can also be explored to capture more complex spatial and contextual information from MRI volumes.

In the future, the system can be integrated with real-time hospital diagnostic systems and cloud-based medical platforms to assist doctors in rapid stroke detection. Additionally, incorporating multi-modal medical data such as CT scans, clinical records, and patient history may further improve prediction reliability and support comprehensive clinical decision-making.

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