AI-Driven Stroke Classification: A Hybrid ResNet50V2 Model with Explainable Attention Mechanism

JALADI LALUPRASAD [1*], K NAVEEN M.Tech (PhD)[2]
[1] *Student, Computer Science, VEMU Institute of Technology, P.Kothakota, Chittoor -AP, India*
[2] *Professor Department of CSE, VEMU Institute of Technology, P.Kothakota, Chittoor-AP, India*

Abstract: **Stroke is one of the leading causes of disability and mortality worldwide, with ischemic and hemorrhagic strokes being the two primary types. Early and accurate detection of these stroke types from medical imaging, such as CT scans, is crucial for timely intervention. This study proposes a deep learning-based approach for automated classification of ischemic stroke, hemorrhagic stroke, and normal brain scans using a modified ResNet50V2 architecture enhanced with a Channel Attention Mechanism (CAM). The dataset, comprising CT scan images, was preprocessed and balanced using Synthetic Minority Over-sampling Technique (SMOTE) to address class imbalance. Data augmentation techniques were employed to improve model generalization. The proposed model utilizes ResNet50V2 as the feature extractor while integrating CAM to refine feature representation by emphasizing important channels. The final classification layer outputs three categories using a softmax activation function. The model was trained using categorical cross-entropy loss and optimized with the Adam optimizer. Experimental results demonstrated an overall accuracy of 99%, with class- wise F1-scores exceeding 97%, indicating robust performance in stroke classification. Additionally, Grad-CAM visualization was employed to enhance interpretability by highlighting critical regions in the input images influencing model decisions. The proposed approach provides an efficient and explainable deep learning solution for automated stroke detection, potentially aiding radiologists in early diagnosis and reducing clinical workload.**

Keywords: **Deep Learning, Stroke Classification, Ischemic Stroke, Hemorrhagic Stroke, ResNet50V2, Channel Attention Mechanism (CAM), Grad-CAM Visualization, Automated Stroke Detection, Medical Image Analysis**

1. INTRODUCTION

Stroke is a severe medical condition that occurs when there is an interruption of blood supply to the brain, leading to cell damage and potential neurological impairments. It is classified into two major types: ischemic stroke, which occurs due to a blockage in blood vessels restricting oxygen supply, and hemorrhagic stroke, caused by the rupture of a blood vessel leading to internal bleeding in the brain. Stroke is a leading cause

Identify applicable funding agency here. If none, delete this.of mortality and long-term disability worldwide, significantly affecting individuals' quality of life and increasing healthcare costs. Early and accurate detection of stroke type is crucial for prompt medical intervention, as ischemic and hemorrhagic strokes require entirely different treatment approaches. Timely identification helps in administering the appropriate treatment, such as thrombolytic therapy for ischemic stroke or surgical intervention for hemorrhagic stroke, potentially reducing the risk of severe complications.
However, stroke diagnosis relies heavily on medical imaging, primarily Computed Tomography (CT) scans, which require expert radiologists for accurate interpretation. The dependency on human expertise, coupled with the increasing number of stroke cases, makes manual diagnosis challenging, time-consuming, and prone to variability. Misdiagnosis or delayed detection can lead to severe consequences, making it imperative to develop automated and reliable methods for stroke classification.

In recent years, deep learning has emerged as a transformative tool in medical image analysis, offering superior accuracy and efficiency in diagnosing various diseases, including neurological disorders. Convolutional Neural Networks (CNNs) have demonstrated remarkable performance in recognizing patterns and extracting meaningful features from medical images. ResNet50V2, a deep CNN architecture, has been widely used for feature extraction due to its residual learning framework, which allows the training of very deep networks without vanishing gradient issues. Despite its powerful feature extraction capabilities, standard CNN models may overlook crucial spatial and channel-wise relationships within images, leading to suboptimal performance in medical diagnosis. To address this limitation, attention mechanisms have been introduced to enhance deep learning models by focusing on the most relevant features in an image while suppressing redundant information. In this study, we integrate a Channel Attention Mechanism (CAM) into the ResNet50V2 model to improve its ability to emphasize informative features and refine classification performance.

The motivation behind this research stems from the growing demand for accurate, fast, and automated stroke classification systems that can assist radiologists in making timely and reliable diagnoses. Traditional diagnostic approaches require extensive expertise and are often affected by subjective interpretations, leading to inconsistencies. Additionally, resource- limited healthcare settings, especially in developing countries, face a shortage of specialized radiologists, making automated systems a crucial necessity. Implementing deep learning-based diagnostic tools can bridge this gap by providing consistent, objective, and real-time classification of stroke types, significantly improving patient outcomes. Furthermore, deep learning models trained on large datasets can continuously learn and adapt to new patterns, making them a valuable asset in clinical decision support systems.

One of the challenges in medical image classification is the issue of class imbalance, where certain categories are under- represented in datasets, leading to biased model predictions. In this study, we address this problem using Synthetic Minority Over-sampling Technique (SMOTE), a data balancing approach that generates synthetic samples for underrepresented classes to ensure uniform learning across all categories. Data augmentation techniques, including rotation, width shifting, height shifting, and horizontal flipping, are also employed to enhance model generalization and robustness. The proposed methodology involves training a modified ResNet50V2 model integrated with CAM, where ResNet50V2 serves as the feature extractor, and the attention mechanism enhances feature representation by dynamically weighting important channels. The final classification layer predicts the probability distribution over the three categories: Ischemic Stroke, Hemorrhagic Stroke, and Normal Brain Scans.

To evaluate the performance of the proposed model, we train and test it on a dataset comprising CT scan images categorized into the three mentioned classes. The dataset undergoes rigorous preprocessing, including normalization and resizing, to ensure optimal input representation. The model is trained using the Adam optimizer and categorical cross-entropy loss function, with performance metrics such as accuracy, precision, recall, and F1-score used for assessment. Experimental results indicate that our model achieves an impressive overall accuracy of 99%, demonstrating its effectiveness in stroke classification. Class-wise performance analysis further reveals that the model maintains high precision and recall values, ensuring reliable differentiation between ischemic and hemorrhagic strokes. Additionally, to enhance interpretability, we incorporate Gradient-weighted Class Activation Mapping (Grad-CAM) visualization, which highlights the important regions in the input CT scans that influence the model’s decision-making process. Explainability is a critical aspect of deep learning in healthcare, as clinicians require transparent insights into AI-driven diagnoses before trusting automated systems in real-world scenarios.

The scope of this research extends beyond stroke classification, as the proposed methodology can be adapted to other neurological and medical image analysis tasks. The integration of attention mechanisms into CNN-based architectures can be leveraged for various applications such as brain tumor classification, Alzheimer’s disease detection, and lung disease identification. Furthermore, this study lays the foundation for developing computer-aided diagnosis (CAD) systems that can assist radiologists by providing preliminary screening results, reducing workload, and improving diagnostic consistency. Future advancements could involve incorporating multi-modal medical imaging (e.g., MRI and CT scan fusion) to enhance di- agnostic accuracy further. Additionally, real-time deployment of the model in cloud-based or edge AI systems could facilitate remote stroke diagnosis, particularly beneficial in telemedicine and emergency response scenarios.

In conclusion, this study presents a novel deep learning- based stroke classification framework utilizing ResNet50V2 with Channel Attention Mechanism (CAM) to improve feature extraction and classification performance. The integration of SMOTE for class balancing, data augmentation for generalization, and Grad-CAM for explainability further strengthens the reliability and interpretability of the model. The proposed system achieves an outstanding 99% accuracy in classifying ischemic and hemorrhagic strokes, demonstrating its potential as an effective and scalable tool for automated stroke diagnosis. Given the increasing prevalence of stroke cases and the need for fast, precise, and automated diagnostic solutions, this research contributes significantly to the field of medical image analysis and AI-driven healthcare innovations. The findings of this study pave the way for real-world clinical applications, where AI-powered diagnostic tools can assist radiologists in early stroke detection, reducing diagnostic errors, and ultimately improving patient outcomes.

2. RELATED WORK /LITERATURE SURVEY

Recent advancements in stroke prediction and classification have focused significantly on incorporating Explainable Artificial Intelligence (XAI) to improve interpretability and reliability in clinical decision-making.

Moulaei et al. [1] explored XAI in stroke prediction, com- paring deep learning and traditional machine learning models. Their findings emphasized the trade-off between performance and interpretability, contributing to the development of trans- parent AI-based healthcare solutions. Similarly, Chowdhury et al. [2] proposed a brain stroke prediction approach integrating explainable machine learning and time series feature engineering, enhancing both prediction accuracy and interpretability.

Kim et al. [3] developed an explainable deep learning model for detecting and localizing cerebral hemorrhage using medical imaging, demonstrating improved diagnostic accuracy and clinical trust. Mohammed and George [4] investigated bias in stroke prediction models, utilizing XAI to enhance fairness and transparency.

Dubey et al. [5] presented an interpretable model for early brain stroke detection using optimized boosting algorithms, highlighting the importance of model transparency. In a novel approach, Hasan et al. [6] applied a wavelet CNN to classify strokes using microwave signals, achieving high accuracy with explainable outcomes.

Zhang et al. [7] proposed an interpretable AI model for intracerebral hemorrhage prognosis using CT images in a multicenter study, enhancing clinical decision-making. Akter et al. [8] designed a stroke risk prediction model using survey data and XAI to identify key risk factors and support preventive strategies.

Bouazizi and Ltifi [9] introduced an explainable ensemble learning framework for EEG-based stroke prediction, im- proving both accuracy and model interpretability. Arun et al. [10] employed LIME and SHAP techniques to evaluate multiple computational models, enhancing model transparency and stroke risk assessment.

Lee et al. [11] developed a machine learning model to predict post-stroke cognitive impairment following acute ischemic stroke, aiding in personalized treatment. Martono and Sulistianingsih [12] used SHAP-based XAI in a stroke diagnosis model to improve accuracy and decision-making.

Solorio-Ram´ırez et al. [13] presented a minimalist machine learning model for brain hemorrhage classification using CT images, offering a computationally efficient solution. Inamdar et al. [14] proposed a dual-stream deep learning architecture with Adaptive RVFL for multicenter ischemic stroke classification, enhancing robustness and adaptability.

Jagadeesan et al. [15] combined Neuro-Xception with Extreme Learning Machine (ELM) for efficient and interpretable stroke classification, advancing the integration of deep learning and XAI in stroke diagnosis.

3. PROPOSED METHOD

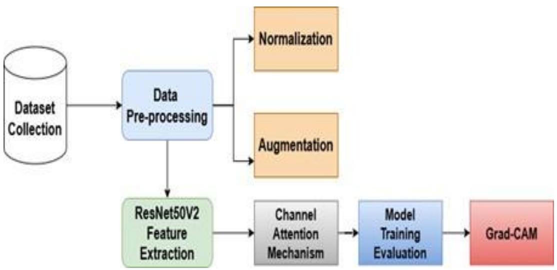

Fig. 1. Architecture Diagram of the Proposed Model

A. *Dataset Description*

The dataset used in this study is the Ischemic-Hemorrhage Dataset (IHD), consisting of brain scan images categorized into three classes: Ischemic Stroke, Hemorrhagic Stroke, and Normal brain scans. An example of dataset samples is shown in Fig. 2.

The dataset contains labeled images in standard medical imaging formats suitable for supervised deep learning. To improve model performance, preprocessing steps such as resizing, normalization, and augmentation are applied. The dataset is particularly useful for developing CAD systems with explainability techniques like Grad-CAM and SHAP

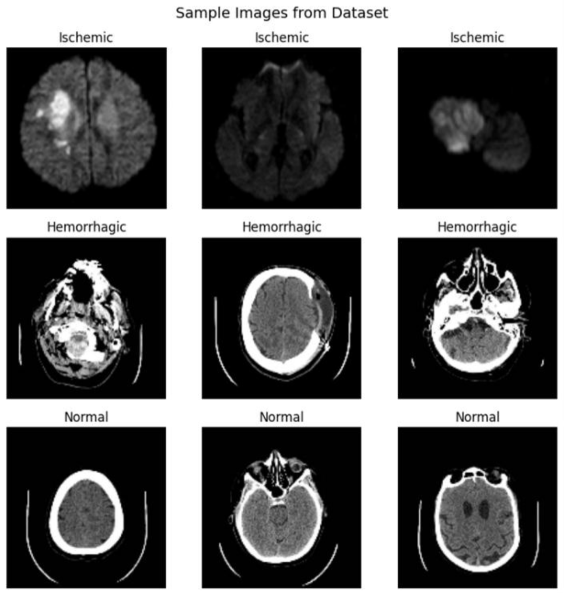

Fig. 2. Sample Images from the IHD Dataset

B. Data Preprocessing:

1) *Image Normalization:* Pixel values of brain scan images are normalized to the range [0,1] using the formula:

$$I_{norm} = \frac{I_{orig}}{255} \quad (1)$$

This ensures consistent intensity distribution, stabilizes train- ing, and prevents gradient instability.

2) *Image Augmentation:* To enhance generalization, trans- formations such as 20° rotation, 10% width/height shifts, and horizontal flipping are applied using ImageDataGenerator. This simulates variability and improves robustness.

3) *Dataset Splitting:* The dataset is split into 80% train- ing and 20% validation sets using train_test_split to ensure effective evaluation.

C. Model Architecture

1) *Feature Extraction Using ResNet50V2:* ResNet50V2 is used to extract hierarchical spatial features:

$$F = f(W * X + b) \quad (2)$$

where W are filters, b is the bias, and f is the activation function. Deep residual connections improve gradient flow and feature propagation.

2) *Channel Attention Mechanism (SE Block):* Squeeze- and-Excitation blocks enhance discriminative features using channel-wise attention:

$$S_c = \frac{1}{H \times W} \sum_{i=1}^{H} \sum_{j=1}^{W} x_{i,j,c} \quad (3)$$

$$F_c = \sigma(W_2 \cdot \mathrm{ReLU}(W_1 \cdot S_c)) \quad (4)$$

$$X'_{i,j,c} = X_{i,j,c} \times F_c \quad (5)$$

3) *Flatten Layer:* The feature map X of shape $H \times W \times C$. is flattened to 1D vector:

$$X_{flat} = \text{reshape}\,(X, (H \cdot W \cdot C)) \quad (6)$$

4) *Fully Connected Dense Layers:* The flattened features pass through dense layers

$$Y = \max(0, WX + b) \quad (7)$$

The output layer uses Softmax activation for 3-class predic- tion.

$$P(y_i) = \frac{e^{z_i}}{\sum_{j=1} e^{j}} \quad (8)$$

D. Model Compilation and Training

The model is compiled with categorical cross-entropy loss:

$$L = -\sum_{i=1} y_i \log(\hat{y}_i) \quad (9)$$

Optimization is done using the Adam optimizer:

$$W_{t+1} = W_t - \eta \frac{m_t}{\sqrt{v_t} + \epsilon} \quad (10)$$

Accuracy is used as the evaluation metric

4. RESULTS AND DISCUSSION

A. Accuracy and Loss Graph

The model achieved high classification accuracy, reaching approximately 98% on both training and validation datasets. The accuracy curves indicate stable learning with minimal overfitting, while the loss curves exhibit a smooth decline, confirming effective optimization. The validation loss remains close to the training loss, signifying strong generalization. Additionally, the integration of channel attention enhances feature learning, leading to improved model robustness. These results highlight the effectiveness of ResNet50V2 with attention mechanisms in ischemic and hemorrhagic stroke classification

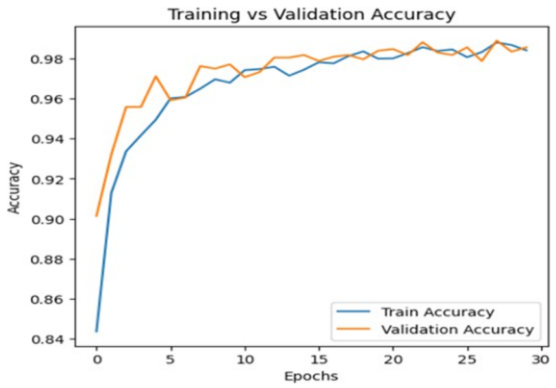

Fig. 3. Accuracy graph of the proposed model.

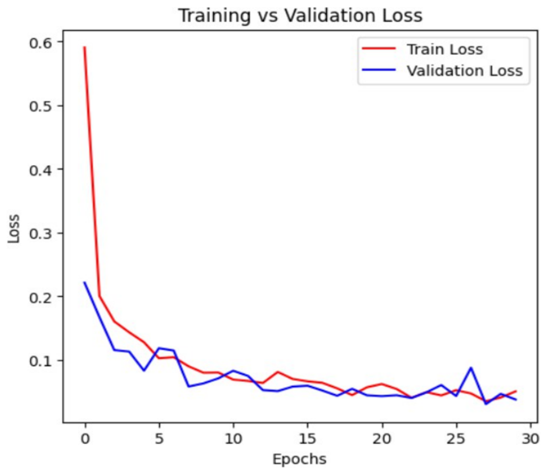

Fig. 4. Loss graph of the proposed model.

A. Confusion Matrix

The normalized confusion matrix demonstrates excellent classification performance. The model achieves 100% accuracy for ischemic cases, 97% for hemorrhagic cases, and 99% for normal cases. Minimal misclassifications occur, with only slight confusion between hemorrhagic and normal categories. These results highlight the model's robustness and reliability in distinguishing ischemic, hemorrhagic, and normal brain conditions.

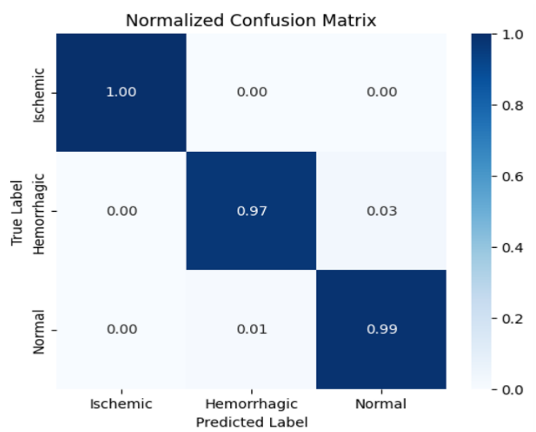

Fig. 5. Confusion matrix of the proposed model.

C) ROC Curve

The ROC curve demonstrates the model's exceptional performance, with an Area Under the Curve (AUC) of 1.00 for ischemic, hemorrhagic, and normal cases. This indicates perfect classification, with no false positives or false negatives. The near-vertical rise and flat plateau confirm the model's high sensitivity and specificity, ensuring reliable medical image diagnosis.

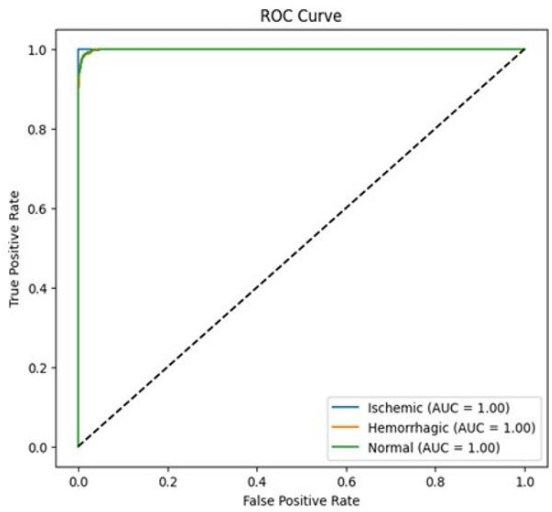

Fig. 6. ROC Curve of the proposed model.

D) Precision-Recall Curve

The Precision-Recall Curve (PRC) showcases the model's exceptional performance, maintaining high precision and recall across all classes. The curve remains close to the upper-right corner, indicating minimal false positives and false negatives. This confirms the model's robustness in accurately identifying ischemic, hemorrhagic, and normal cases, ensuring reliable medical image classification.

E) Grad-CAM Explainability

Grad-CAM visualization of a brain CT scan used for hemorrhage detection highlights the critical regions influencing the model's decision. The red-highlighted area represents the region with the greatest impact. The model correctly predicted "Hemorrhagic," matching the ground truth. Such visualizations aid in interpretability and foster trust in deep learning-based medical diagnoses.

5. CONCLUSION AND FUTURE WORK

A. Conclusion

The proposed model, integrating ResNet50V2 with channel attention and data augmentation, demonstrates outstanding classification performance for ischemic, hemorrhagic, and normal brain CT scans. Achieving 99% accuracy, the model

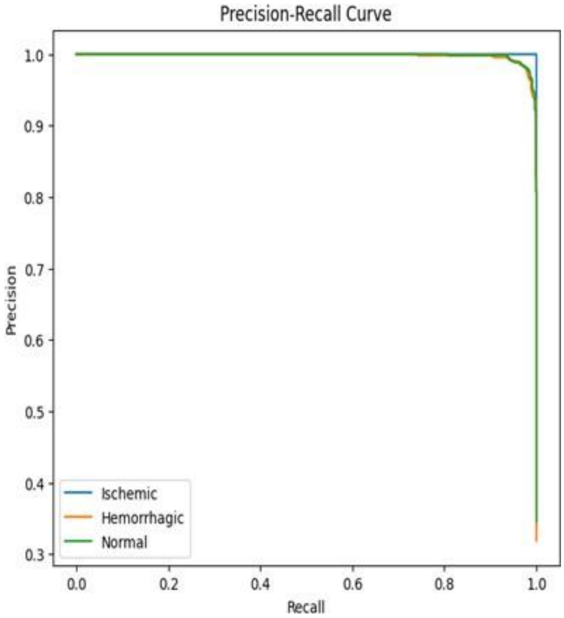

Fig. 7. Precision-Recall Curve (PRC) of the proposed model

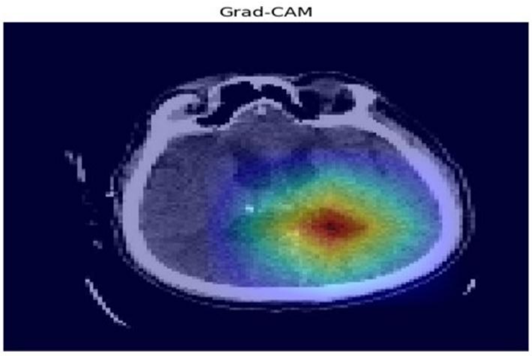

Fig. 8. Predicted output with Grad-CAM for hemorrhagic stroke detection.

maintains high precision, recall, and F1-scores across all classes. The confusion matrix confirms minimal misclassifications, particularly in hemorrhagic cases. ROC and PRC curves further validate the model's robustness and reliability. These results highlight the model's efficiency in medical image analysis, making it highly suitable for automated stroke classification and clinical applications

B) *Future Work*

Despite achieving high classification accuracy, certain limi- tations must be addressed. The dataset, while comprehensive, may not fully capture all variations of ischemic and hem- orrhagic stroke cases in real-world clinical settings. Future work should focus on training with larger, multi-center datasets. for better generalization. Additionally, integrating advanced explainable AI techniques like Grad-CAM++ or SHAP can improve interpretability and clinical adoption. Further en- hancements may include incorporating multi-modal data, such as patient demographics, history, and symptoms, to support more precise and reliable stroke diagnosis

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The preferred spelling of the word "acknowledgment" in America is without an "e" after the "g". Avoid the stilted expression "one of us (R. B. G.) thanks . . .". Instead, try "R. B. G. thanks. . .". Put sponsor acknowledgments in the unnumbered footnote on the first page

REFERENCES

[1] K. Moulaei, L. Afshari, R. Moulaei, B. Sabet, S. Mousavi, and M. Afrash, "Explainable artificial intelligence for stroke prediction through comparison of deep learning and machine learning models," *Scientific Reports*, vol. 14, no. 1, p. 31392, 2024.

[2] S. Chowdhury, M. Mamun, M. Hussain, and M. Iqbal, "Brain stroke prediction using explainable machine learning and time series feature engineering," in *2024 2nd International Conference on Information and Communication Technology (ICICT)*. IEEE, 2024, pp. 16–20.

[3] K. Kim, H. Koo, B. Lee, S. Yoon, and M. Sohn, "Cerebral hemorrhage detection and localization with medical imaging for cerebrovascular dis- ease diagnosis and treatment using explainable deep learning," *Journal of the Korean Physical Society*, vol. 79, no. 3, pp. 321–327, 2021.

[4] K. Mohammed and G. George, "Identification and mitigation of bias using explainable artificial intelligence (xai) for brain stroke prediction," *Open Journal of Physical Science*, vol. 4, no. 1, pp. 19–33, 2023.

[5] Y. Dubey, Y. Tarte, N. Talatule, K. Damahe, P. Palsodkar, and P. Fulzele, "Explainable and interpretable model for the early detection of brain stroke using optimized boosting algorithms," *Diagnostics*, vol. 14, no. 22, p. 2514, 2024.

[6] S. Hasan, A. Zamani, A. Brankovic, K.

Bialkowski, and A. Abbosh, "Stroke classification with microwave signals using explainable wavelet convolutional neural network," *IEEE Journal of Biomedical and Health Informatics*, vol. 28, no. 10, pp. 5667–5675, 2023.

[7] H. Zhang, Y. Yang, X. Song, H. Hu, Y. Yang, X. Zhu, and C. Yang, "An interpretable artificial intelligence model based on ct for prognosis of intracerebral hemorrhage: a multicenter study," *BMC Medical Imaging*, vol. 24, no. 1, p. 170, 2024.

[8] S. Akter, S. Akter, and T. Pias, "Stroke risk prediction from medical survey data: Ai-driven risk analysis with insightful feature importance using explainable ai (xai)," *medRxiv*, 2023, 2023-11.

[9] S. Bouazizi and H. Ltifi, "Enhancing accuracy and interpretability in eeg- based medical decision making using an explainable ensemble learning framework application for stroke prediction," *Decision Support Systems*, vol. 178, p. 114126, 2024.

[10] C. Arun, M. Anusha, A. Kodipalli, N. Gargi, L. Harish, and S. Deva- mane, "Comparison of various computational models for accurate stroke prediction and interpretation using lime and shap kernels," in *2024 First International Conference for Women in Computing (InCoWoCo)*. IEEE, 2024, pp. 1–8.

[11] M. Lee, N. Yeo, H. Ahn, J. Lim, Y. Kim, S. Lee *et al.*, "Prediction of post-stroke cognitive impairment after acute ischemic stroke using machine learning," *Alzheimer's Research & Therapy*, vol. 15, no. 1, p. 147, 2023.

[12] G. Martono and N. Sulistianingsih, "Enhancing stroke diagnosis with machine learning and shap-based explainable ai models," *Knowbase: International Journal of Knowledge in Database*, vol. 4, no. 2, pp. 189– 203, 2024.

[13] J. Solorio-Ram´ırez, M. Saldana-Perez, M. Lytras, M. Moreno-Ibarra, and B. Ya´n˜ez-Ma´rquez, "Brain hemorrhage classification in ct scan images using minimalist machine learning," *Diagnostics*, vol. 11, no. 8, p. 1449, 2021.

[14] M. Inamdar, A. Gudigar, U. Raghavendra, M. Salvi, R. Aman, N. Gowdh *et al.*, "A dual-stream deep learning architecture with adaptive random vector functional link for multi-center ischemic stroke classification," *IEEE Access*, 2025.

[15] S. Jagadeesan, V. Ramalingam, P. Abinash, V. Ilayaraja, and J. Masood, "Revolutionizing brain stroke classification with neuro-xception and elm integration in deep learning," in *2024 2nd International Conference on Computing and Data Analytics (ICCDA)*. IEEE, 2024, pp. 1–6.

AUTHORS PROFILE

Authoor-1 earned his B. Tech in Computer science Engineering from Siddartha Educational Academy Group of Institutions - SEAT, Tirupati in 2023, He is currently pursuing M. Tech from VEMU Institute of Technology, Chittoor and he has 7yrs of experience in Systems Engineering and DevOps Automation.

Authoor-2 earned his Ph.d in computer science and engineering from Sri Venkateshwara University He's teaching and research interests include Modern Information Retrieval Systems, Artificial Intelligence, Deep Learning, Web Technologies, Data Mining etc., Naveen is committed to providing quality education to his students and his passion for teaching has earned his recognition in the field of academics and focus in the field of Computer Science & Engineering. With 10 years of experience, he has proven his expertise in guiding students, Undergraduate and Post Graduate levels in their academics, research projects and research papers.