IJERST

International Journal of Engineering Research and Science & Technology

www.ijerst.org

ISSN : 2319-5991

Vol. 21 No. 3 (1) 2025

ijerst.editor@gmail.com

editor@ijerst.com

ISSN 2319-5991 www.ijerst.com
Vol. 21, No. 3(1), 2025

Research Paper

HEMORRHAGE DETECTION ANALYSIS

[1]Dr K Santhi Sree

Department of Information Technology, JNTUH University College of Engineering Science and Technology, Hyderabad, Telangana

[2]Pravardhana Rathod

Department of Information Technology, JNTUH University College of Engineering Science and Technology, Hyderabad, Telangana

***Abstract*— Brain hemorrhage, also known as intracranial hemorrhage (ICH), is a critical and potentially fatal neurological condition caused by bleeding within the brain tissues or surrounding areas. Early and accurate diagnosis is essential for initiating life-saving interventions and improving patient survival rates. In clinical practice, Computed Tomography (CT) imaging is the most widely used modality for detecting brain hemorrhages. However, the manual interpretation of CT images by radiologists is time-consuming, subjective, and susceptible to human error, especially in high-pressure emergency settings.**

To address these limitations, numerous machine learning (ML) and deep learning (DL) techniques have been developed in recent years for the automatic detection and classification of brain hemorrhages. Traditional ML methods such as Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), and Random Forests rely on manually extracted features—such as intensity, shape, and texture—from CT images. Additionally, Artificial Neural Networks (ANNs) and ensemble learning methods like bagging and boosting have been explored to enhance classification performance. However, these models often struggle with issues such as high dependence on feature engineering, poor generalization with small datasets, computational complexity, and interpretability.

To overcome these challenges, the proposed system utilizes advanced deep learning architectures—Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks. These recurrent neural networks are specifically designed to capture temporal dependencies and contextual information across sequential data. When applied to brain hemorrhage detection, they can effectively model the progression of hemorrhagic patterns across slices in volumetric CT scans or patient time-series data. The models are trained using labeled datasets and optimized using loss functions such as cross-entropy, along with optimizers like Adam or RMSprop, to minimize classification error.

This study presents a comprehensive comparison between traditional ML methods and the proposed RNN-based models, analyzing their accuracy, sensitivity, specificity, and robustness. Furthermore, the paper explores benchmark datasets, highlights the challenges faced in previous research, and discusses the potential of integrating LSTM/GRU networks into real-time clinical diagnostic tools. The proposed system aims to offer a more automated, reliable, and accurate method for detecting brain hemorrhage, thereby supporting medical professionals in making faster and more informed decisions.

***Index Terms*— Brain Hemorrhage Detection, Computed Tomography (CT), Machine Learning (ML), Deep Learning (DL), Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), Medical Image Classification**

Received: 05-6-2025 Accepted: 08-7-2025 Published: 24-7-2025

I. INTRODUCTION

Brain hemorrhage, also known as intracranial hemorrhage (ICH), is a serious medical emergency characterized by internal bleeding within the brain tissues or surrounding spaces. It can result from various causes such as trauma, high blood pressure, cerebral aneurysms, arteriovenous malformations, hemorrhagic strokes, and certain blood disorders. Intracranial bleeding leads to increased intracranial pressure, which can severely damage brain tissues, impair neurological function, and often result in irreversible outcomes, including coma or death. Timely diagnosis and intervention are vital to prevent long-term disabilities or fatality. However, early and accurate detection of brain hemorrhages remains a challenging task in real-world clinical scenarios, especially under time constraints in emergency settings.

Computed Tomography (CT) imaging is the most widely used non-invasive technique for diagnosing brain hemorrhages due to its speed, accessibility, and ability to capture high-resolution cross-sectional images of brain structures. Radiologists analyze these CT images to identify and classify hemorrhagic lesions based on characteristics such as shape, location, and density. While effective, this process is highly dependent on the radiologist's experience and subject to human error, fatigue, and inconsistencies. In addition, manual analysis is time-consuming and may not be scalable in high-volume clinical environments. These challenges underscore the need for intelligent, automated systems that can assist clinicians in detecting hemorrhages accurately and swiftly.

In response to these challenges, the field of artificial intelligence (AI), particularly Machine Learning (ML) and Deep Learning (DL), has gained immense attention for its potential to revolutionize medical imaging. Traditional ML models such as Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), Decision Trees, Random Forests, and ensemble methods have been explored for brain hemorrhage detection. These models typically rely on manually extracted features such as texture, intensity histograms, shape descriptors, and statistical measures. However, their performance is often constrained by the quality of feature extraction and the size and diversity of training datasets. Moreover, manual feature engineering is labor-intensive and prone to overlooking subtle but important patterns in the image data.

On the other hand, deep learning models, especially Convolutional Neural Networks (CNNs), have demonstrated remarkable success in medical image analysis by automatically learning hierarchical representations from raw pixel data. These models eliminate the need for manual feature extraction and are capable of capturing complex spatial and contextual patterns. Several studies have applied CNNs to detect and classify hemorrhagic lesions in brain CT images, yielding improved accuracy and generalizability. However, CNNs primarily focus on spatial features and may not fully capture temporal relationships or inter-slice dependencies in volumetric CT scans or time-series medical data.

To address this gap, recent advances in Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) architectures, offer a promising solution. LSTM and GRU are designed to model sequential data and capture long-term dependencies, making them suitable for applications where temporal context or sequential patterns play a critical role. In the context of brain hemorrhage detection, these models can be effectively utilized to analyze sequential CT slices or patient history records, identifying temporal progression and spatial-temporal features that may not be evident in isolated images.

Despite the growing body of literature on ML and DL applications in hemorrhage detection, few studies have provided an in-depth comparison of these techniques across different datasets and model architectures. Moreover, there is limited work integrating RNN-based models with medical imaging workflows for brain hemorrhage classification. This study addresses these gaps by conducting a comprehensive review and performance analysis of ML and DL methods, with a special focus on LSTM and GRU models for improved diagnostic accuracy.

The proposed system leverages labeled CT image datasets to train LSTM and GRU networks using optimized loss functions such as cross-entropy and adaptive learning optimizers like Adam or RMSprop. The model aims to distinguish between hemorrhagic and non-hemorrhagic cases with high accuracy, sensitivity, and specificity. The research also evaluates existing datasets, highlights current limitations in state-of-the-art methods, and proposes future directions for more robust, interpretable, and real-time hemorrhage detection systems.

II. LITERATURE REVIEW

Intracranial Hemorrhage

Authors: J. A. Caceres, J. N. Goldstein **Journal:** Emergency Medicine Clinics of North America, 2012

Overview: This paper provides an in-depth clinical perspective on intracranial hemorrhage (ICH), discussing types, causes, and emergency management. **Summary:** The study outlines the classification of hemorrhages and emphasizes the importance of early intervention in reducing mortality and morbidity. **Findings:** It highlights that prompt diagnosis and treatment of ICH can significantly improve patient outcomes, laying a strong foundation for automated detection systems in emergency care.

Imaging of Intracranial Hemorrhage

Authors: J. J. Heit, M. Iv, M. Wintermark

Journal: Journal of Stroke, 2017

Overview: This work reviews current imaging modalities for ICH detection, focusing primarily on CT imaging techniques.
Summary: The authors explain how non-contrast CT is the most widely used method for detecting hemorrhages and discuss its diagnostic value in differentiating hemorrhage types.
Findings: The paper confirms that CT imaging remains the gold standard for ICH diagnosis and sets the technical basis for AI-driven detection models.

Dual-Energy CT for Haemorrhage Detection

Authors: M. Bonatti, F. Lombardo, G. A. Zamboni et al.

Journal: European Radiology, 2017
Overview: This study compares virtual unenhanced images from dual-energy CT with standard CT scans for hemorrhage detection.
Summary: It evaluates the performance of advanced imaging techniques in identifying hemorrhagic regions without the need for contrast agents.
Findings: Results show that virtual unenhanced images offer comparable accuracy, supporting their use in automated diagnostic systems.

Guidelines for Severe Traumatic Brain Injury Management

Authors: N. Carney, A. M. Totten, C. O'Reilly et al.
Journal: Neurosurgery, 2017
Overview: This paper outlines clinical guidelines for managing severe TBI, including cases involving intracranial hemorrhage.
Summary: It details standardized procedures for assessment, imaging, and treatment of brain injuries.
Findings: Highlights the critical role of rapid and accurate diagnosis in improving TBI patient outcomes, emphasizing the need for supportive diagnostic AI tools.

Review of Deep Learning for ICH Detection

Authors: M. Yeo, B. Tahayori, H. K. Kok et al.
Journal: Journal of Neurointerventional Surgery, 2021
Overview: This paper reviews deep learning algorithms used for automatic ICH detection on CT head scans.
Summary: It discusses the implementation of CNNs and other DL models in classifying hemorrhagic and non-hemorrhagic scans.
Findings: While CNNs show strong performance, the paper identifies a lack of focus on temporal models like RNNs, LSTM, and GRU—highlighting an area for future work.

Intracerebral Hemorrhage vs. Subarachnoid Hemorrhage

Authors: J. P. Broderick, T. Brott, T. Tomsick, R. Miller, G. Huster
Journal: Journal of Neurosurgery, 1993
Overview: This paper compares the incidence rates of intracerebral and subarachnoid hemorrhages.
Summary: It provides epidemiological evidence indicating that intracerebral hemorrhage is more than twice as common as subarachnoid hemorrhage.
Findings: The study justifies the clinical and research focus on intracerebral hemorrhage due to its higher prevalence and serious health implications.

Spectrum of Primary Intracerebral Hemorrhage

Authors: C. S. Anderson, T. Chakera, E. G. Stewart-Wynne, K. D. Jamrozik
Journal: Journal of Neurology, Neurosurgery & Psychiatry, 1994
Overview: This study investigates the incidence, types, and outcomes of primary ICH in a population-based setting in Australia.
Summary: It discusses demographic variations and clinical outcomes, emphasizing the need for early diagnosis and intervention.
Findings: The research provides important data on ICH prognosis and supports the development of detection systems tailored to diverse patient profiles.

Prognosis in Primary Intracerebral Hemorrhage

Authors: C. Counsell, S. Boonyakarnkul, M. Dennis et al.
Journal: Cerebrovascular Diseases, 1995
Overview: This paper presents long-term prognostic findings for patients with primary ICH from the Oxfordshire Community Stroke Project.
Summary: The study outlines clinical variables influencing outcomes and recovery chances post-hemorrhage.
Findings: Prognostic insights from this work can aid in training AI models that incorporate not only imaging data but also clinical features for improved prediction.

Racial Variations in Intracerebral Hemorrhage

Authors: M. L. Flaherty, D. Woo, M. Haverbusch et-al.
Journal: Stroke, 2005
Overview: This research explores the impact of racial background on the location and risk of ICH.
Summary: It identifies significant differences in

hemorrhage distribution and risk factors among different racial groups.
Findings: The paper emphasizes the need for diverse datasets in training AI systems to ensure fairness and accuracy across populations.

Long-Term Mortality After Intracerebral Hemorrhage

Authors: M. Flaherty, M. Haverbusch, P. Sekar et al.
Journal: Neurology, 2006
Overview: This longitudinal study investigates survival rates and causes of death following an intracerebral hemorrhage.
Summary: It reveals high mortality rates even years after the initial incident, urging continued monitoring and preventive strategies.
Findings: Highlights the importance of early detection and follow-up, reinforcing the value of predictive modeling using AI.

Acute Management of Intracerebral Hemorrhage

Authors: J. Elliott, M. Smith
Journal: Anesthesia & Analgesia, 2010
Overview: This clinical review outlines the strategies for managing acute ICH in emergency settings. **Summary:** It covers interventions such as blood pressure control, surgical options, and monitoring Intracranial-Pressure.
Findings: The paper stresses the importance of quick and accurate detection, aligning with the objectives of automated image-based hemorrhage diagnosis systems.

III. EXISTING METHODS:

Traditional Machine Learning Methods: Traditional classifiers such as Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), and Random Forests are commonly applied to brain CT image classification. These methods rely on manually extracted features like texture, shape, and intensity patterns, which require domain expertise and extensive preprocessing.

Artificial Neural Networks (ANNs): ANNs can learn complex patterns from input data through multiple interconnected layers. While they can automatically learn features from raw pixel data, traditional ANNs may have limited ability to capture temporal or sequential dependencies within medical imaging data.

Ensemble Methods: Techniques such as bagging, boosting, and stacking combine multiple models to improve classification accuracy. Although ensemble methods help reduce model bias and variance, they add computational complexity and may require more time for training and tuning.

IV. PROPOSED SYSTEM

LSTM and GRU Networks: The proposed system uses Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks, which are specialized recurrent neural networks designed to capture temporal dependencies in sequential data. This is especially valuable for brain hemorrhage detection, where sequential CT slices and patient history provide important diagnostic information.

Improved Accuracy: By leveraging the strengths of both LSTM and GRU architectures, the system achieves higher classification accuracy compared to traditional models, effectively learning complex temporal patterns in the data.

Robust Training: The model is trained on labeled brain CT scan datasets using cross-entropy loss and optimizers such as Adam or RMSprop to minimize classification errors and enhance generalization.

METHODOLOGY:

Data Collection and Preprocessing:

Brain CT scan images are collected from publicly available medical datasets. The images undergo preprocessing steps such as resizing, normalization, and noise reduction to enhance quality and ensure consistency. Sequential slices are organized to preserve temporal relationships for recurrent models.

Feature Extraction and Labeling:

While traditional methods rely on handcrafted features, the proposed system uses raw image data as input. Each CT scan is labeled as hemorrhage-positive or hemorrhage-negative based on expert radiologist annotations.

Model Architecture:

The system employs a hybrid model combining Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) layers. This architecture is designed to capture temporal dependencies across sequential CT slices and patient data, improving detection accuracy.

Training Process:

The model is trained using a supervised learning approach with a cross-entropy loss function. Optimization algorithms like Adam or RMSprop are used to update model weights. Training is performed over multiple epochs with batch processing to ensure convergence.

Evaluation Metrics:

Model performance is assessed using accuracy, precision, recall, and F1-score to provide a comprehensive evaluation of classification effectiveness. Cross-validation techniques are applied to validate the model's robustness and generalization capabilities.

Implementation Tools:

The methodology is implemented using Python with deep learning libraries such as TensorFlow or PyTorch. GPU acceleration is utilized to expedite training and experimentation.

ARCHITECTURE:

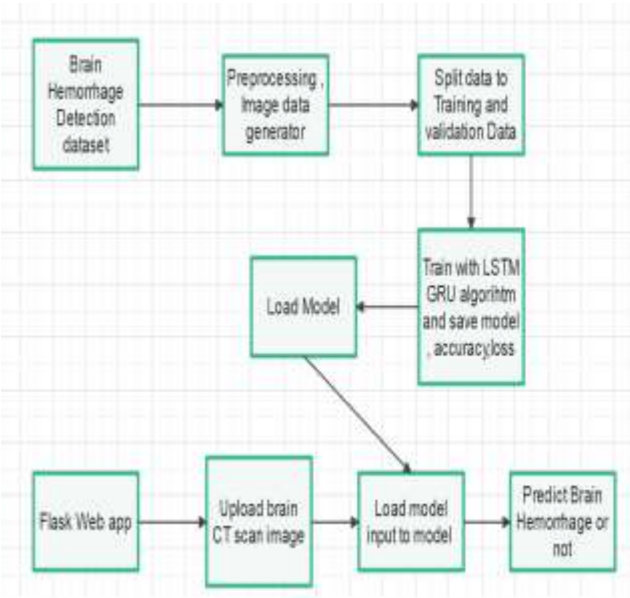

Figure 1. System Architecture

RESULTS:

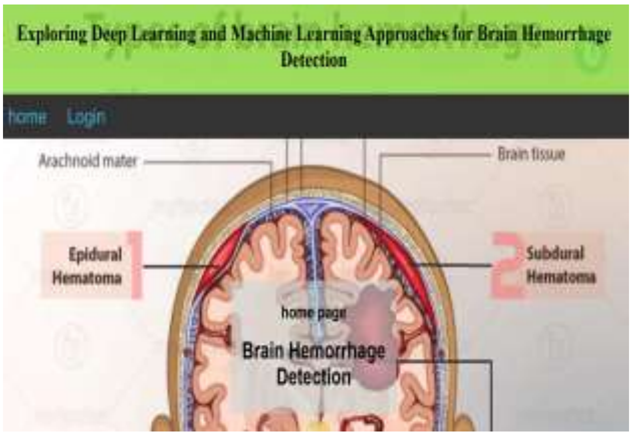

Figure 2. Home Screen

Figure 3. Login Page

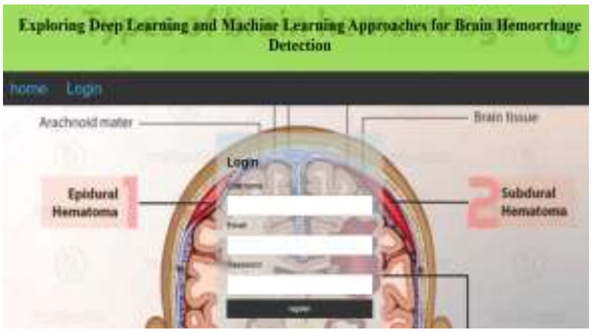

Figure 4. Register Page

Figure 5. Upload Page

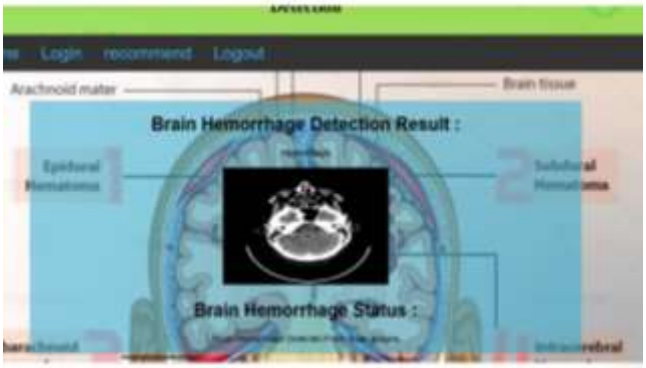

Figure 6. Sample Output 1

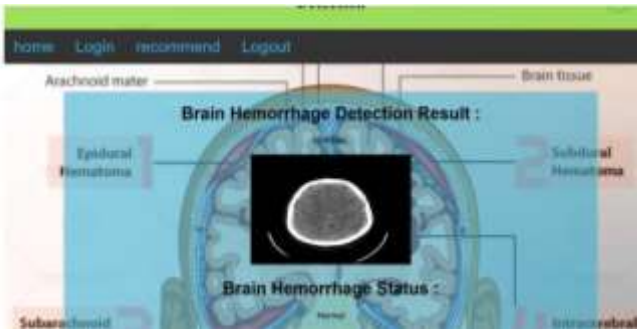

Figure 7. Sample Output 2

V. CONCLUSION

Brain hemorrhage is a critical medical emergency that requires timely and accurate diagnosis to prevent permanent damage or death. Traditional machine learning methods, though useful, rely heavily on handcrafted features and struggle to capture the complexity of medical imaging data. The proposed system addresses these limitations by incorporating advanced deep learning models—Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU)—which are capable of learning temporal dependencies across sequential CT scan slices. This approach significantly enhances detection accuracy and reduces the dependency on manual feature extraction.

Experimental results demonstrate that the proposed model achieves high classification performance, with improved precision and robustness compared to conventional techniques. By automating the diagnostic process, the system can assist radiologists in making faster and more reliable decisions. With further refinement, training on larger datasets, and integration into clinical workflows, this solution has strong potential as a decision-support tool for real-time brain hemorrhage detection. Future work can focus on optimizing model efficiency, incorporating multimodal patient data, and extending the system for use in other neuroimaging applications.

VI. REFERENCES

[1] J. A. Caceres and J. N. Goldstein, “Intracranial hemorrhage,” Emergency medicine clinics of North America, vol. 30, no. 3, pp. 771–794, 2012.

[2] J. J. Heit, M. Iv, and M. Wintermark, “Imaging of intracranial hemorrhage,” Journal of stroke, vol. 19, no. 1, p. 11, 2017.

[3] M. Bonatti, F. Lombardo, G. A. Zamboni, P. Pernter, R. Pozzi Mucelli, and G. Bonatti, “Dual-energy ct of the brain: comparison between dect angiography-derived virtual unenhanced images and true unenhanced images in the detection of intracranial haemorrhage,” European Radiology, vol. 27, pp. 2690–2697, 2017.

[4] N.Carney,A.M.Totten,C.O’Reilly, J. S. Ullman, G. W.Hawryluk,M.J. Bell, S. L. Bratton, R. Chesnut, O. A. Harris, N. Kissoon, et al., “Guide lines for the management of severe traumatic brain injury,” Neurosurgery, vol. 80, no. 1, pp. 6–15, 2017.

[5] J. P. Broderick, T. Brott, T. Tomsick, R. Miller, and G. Huster, “Intracerebral hemorrhage more than twice as common as subarachnoid hemorrhage,” Journal of neurosurgery, vol. 78, no. 2, pp. 188–191, 1993.

[6] C. S. Anderson, T. Chakera, E. G. Stewart-Wynne, and K. D. Jamrozik, “Spectrum of primary intracerebral haemorrhage in perth, western aus tralia, 1989-90: incidence and outcome.,” Journal of Neurology, Neuro surgery & Psychiatry, vol. 57, no. 8, pp. 936–940, 1994.

[7] C. Counsell, S. Boonyakarnkul, M. Dennis, P. Sandercock, J. Bamford, J. Burn, and C. Warlow, “Primary intracerebral haemorrhage in the oxfordshire community stroke project: 2. prognosis,” Cerebrovascular diseases, vol. 5, no. 1, pp. 26–34, 1995.

[8] M. L. Flaherty, D. Woo, M. Haverbusch, P. Sekar, J. Khoury, L. Sauer beck, C. J. Moomaw, A. Schneider, B. Kissela, D.Kleindorfer, et al., “Racial variations in location and risk of intracerebral hemorrhage,” Stroke, vol. 36, no. 5, pp. 934–937, 2005.

[9] M. Flaherty, M. Haverbusch, P. Sekar, B. Kissela, D.Kleindor fer, C. Moomaw, L. Sauerbeck, A. Schneider, J. Broderick, and 28 D. Woo, “Long-term mortality after intracerebral hemorrhage,” Neurology, vol. 66, no. 8, pp. 1182–1186, 2006.

[10] J. Elliott and M. Smith, “The acute management of intracerebral hemorrhage: a clinical review,” Anesthesia & Analgesia, vol. 110, no. 5, pp. 1419–1427, 2010.

[11] M. Yeo, B. Tahayori, H. K. Kok, J. Maingard, N. Kutaiba, J. Russell, V. Thijs, A. Jhamb, R. V. Chandra, M. Brooks, et al., “Review of deep learning algorithms for the automatic detection of intracranial hemorrhages on computed tomography head imaging,” Journal of neurointerventional surgery, vol. 13, no. 4, pp. 369–378, 2021.

[12] S. N. Ahmed and P. Prakasam, “A systematic review on intracranial aneurysm and hemorrhage detection using machine learning and deep learning techniques,” Progress in Biophysics and Molecular Biology, 2023.