Intracranial Hemorrhage (ICH) Detection and Classification using Deep Learning.

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Abstract
Intracranial Hemorrhage (ICH) is a life threatening condition that requires rapid and accurate diagnosis to improve patient outcomes. Traditional diagnostic methods relying on manual interpretation of CT and MRI scans are often time-consuming and susceptible to human error, especially in emergency settings. This project proposes the development of an intelligent, deep learning-based system for the automated detection and classification of ICH. Leveraging convolutional neural networks (CNNs) or hybrid models, the system aims to identify the presence of hemorrhage, perform binary and multiclass classification of hemorrhage types, and quantify the affected brain volume. By integrating both CT and MRI data, the system seeks to enhance diagnostic precision and support clinical decision-making, ultimately contributing to improved healthcare delivery.

Keywords
Intracranial Hemorrhage (ICH), Deep Learning, Medical Image Analysis, CT Scan, MRI Scan, Hemorrhage Classification, Convolutional Neural Networks (CNN)

Introduction

Intracranial Hemorrhage (ICH) refers to bleeding within the skull and is considered a critical neurological emergency that can result from trauma, hypertension, aneurysms, or vascular abnormalities. Early and precise detection of ICH is essential to prevent severe neurological damage and mortality. Magnetic Resonance Imaging(MRI) and Computed Tomography(CT) are the primary imaging modalities used for the detection of hemorrhages due to their ability to provide detailed views of brain structures and abnormalities.

In current clinical practice, radiologists manually interpret these scan images to diagnose and classify ICH, a process that is time-consuming and subject to inter-observer variability. The rapid influx of imaging data in emergency departments further strains diagnostic efficiency. To address these challenges, there is a growing interest in employing Artificial Intelligence techniques, particularly deep learning, to automate the detection and classification of ICH from neuroimaging data.

Deep learning models like Convolutional Neural Networks (CNNs), have demonstrated exceptional performance in medical image analysis tasks. These models are capable of learning hierarchical features directly from raw imaging data, facilitating precise identification of subtle patterns linked to different types of hemorrhages. This project intends to develop an automated, intelligent system using deep learning methods for the identification and categorization of ICH from CT and MRI scans. The system is designed to perform both binary (hemorrhage vs. no hemorrhage) and multiclass classification (subtypes of hemorrhage), while also quantifying the percentage of brain volume affected.

By integrating such AI-driven tools into clinical workflows, the goal is to support radiologists in making quicker and more accurate decisions, thereby improving patient outcomes and reducing diagnostic delays.

Literature Review

Several studies have explored the use of machine learning (ML) and deep learning (DL) techniques for the detection and categorization of intracranial hemorrhage (ICH) using CT and MRI images. These methods have aimed to improve diagnostic accuracy, reduce processing time, and support clinical decision-making.

Rani and Mohan (2022) proposed a deep learning rooted approach for detecting brain hemorrhages, demonstrating the capability of AI to assist in early diagnosis. Their model utilizes convolutional neural networks (CNNs) to analyze CT scan images, effectively identifying the presence of hemorrhages. The approach emphasizes the importance of rapid and accurate detection, which is crucial for timely medical intervention. By automating the detection process, their work aims to support healthcare professionals in making informed decisions swiftly. [1]

Majeed et al. (2023) introduced a system that combines multiple features extracted from CT images with machine learning (ML) algorithms for effective classification of intracranial hemorrhage (ICH) types. Their work emphasizes feature selection and its impact on model accuracy. They employed methods to extract relevant features from CT images, which were then used to train machine learning models for classifying different ICH types. The study highlights the significance of selecting appropriate features to enhance the performance and precision of the classification system. [2]

Tanwar et al. (2024) focused on using Convolutional Neural Networks (CNNs) in intelligent environments to advance healthcare applications, particularly in emergency diagnosis. They explored the potential of CNNs to analyze medical images, facilitating the detection of conditions such as brain hemorrhages. Their research underscores the role of deep learning in transforming healthcare diagnostics, making them more efficient and accessible, especially in emergency settings. [3]

Rooshita et al. (2024) implemented a web-based system using deep learning for real-time hemorrhage detection, offering both accessibility and scalability in medical settings. Their system allows healthcare professionals to upload CT scan images to a web platform, where deep learning models analyze the images to detect the presence of hemorrhages. This approach enhances the accessibility of advanced diagnostic tools, enabling timely interventions even in resource-limited settings. [4]

Emon et al. (2023) proposed a hybrid approach combining machine learning (ML) and deep learning (DL) techniques 3 to increase the performance of ICH diagnosis and classification systems. Their method integrates handcrafted and features using deep representations, aiming to leverage the strengths of both ML and DL. The study demonstrates the benefits of combining traditional machine learning techniques with modern deep learning approaches to improve diagnostic accuracy and robustness. [5]

Al Okashi et al. (2019) employed ensemble learning methods on MRI data, showing improvements in robustness and accuracy through model aggregation. They combined multiple machine learning models to create an ensemble that can more effectively classify ICH types from MRI scans. The ensemble approach helps mitigate the weaknesses of individual models, leading to more reliable and accurate predictions. Their work highlights the effectiveness of ensemble 4 learning image analysis. [6]

Lewick et al. (2020) utilized deep learning for intracranial hemorrhage detection in CT scans, advancing beyond earlier approaches that depended on traditional machine learning methods such as SVMs and decision trees, which required manual feature extraction. By implementing convolutional neural networks (CNNs), they enabled automated learning of complex features directly from raw CT images. Their methodology also incorporated transfer learning and data augmentation techniques, using datasets like the RSNA Intracranial Hemorrhage Detection dataset to enhance model accuracy. This work demonstrates the shift toward more automated and accurate image analysis in medical diagnostics. [7]

Thongseesang et al. developed an AI-based automated framework for detecting mild traumatic brain injury (mTBI), building on prior research that applied deep learning to neurological imaging. Earlier studies used MRI, DTI, and EEG data with models like CNNs and residual networks to identify subtle brain changes. Some also explored multimodal and unsupervised approaches to enhance model robustness and reduce dependency on labeled data. Emphasis on interpretable AI further supported clinical relevance. These developments laid the groundwork for Thongseesang et al.'s more accurate and accessible mTBI detection system. [8]

Maghami et al. (2023) conducted a systematic review and meta-analysis to assess the diagnostic accuracy of machine learning algorithms for intracranial hemorrhage (ICH) detection. Building on previous research that applied ML and CNNs to CT imaging, their study synthesizes findings from various models that reported high sensitivity and specificity. While earlier works showed promising results, they differed in algorithm types, datasets, and evaluation methods. Maghami et al. addressed these inconsistencies by providing a consolidated analysis and emphasizing the need for methodological standardization in future ML-based diagnostic studies. [9]

Fernando et al. (2021) explored the relationship between intracerebral hemorrhage (ICH) incidence, mortality, and oral anticoagulant (OAC) use, building on earlier research into global ICH trends and the risks associated with different anticoagulants. Previous studies had highlighted changing patient profiles, variable outcomes based on anticoagulant type, and the severity of ICH in anticoagulated populations. By synthesizing these findings, Fernando et al. contributed valuable insights into how OACs influence ICH risk and outcomes, supporting more informed clinical decisions and preventive strategies. [10]

Bhadauria et al. (2021) proposed a method for hemorrhage detection that combines edge-based contour extraction with fuzzy clustering, building on earlier work in automated brain CT analysis. Previous studies used techniques like thresholding, region growing, and clustering algorithms such as k-means and fuzzy c-means to segment hemorrhagic regions, often facing challenges from image noise and variability. By integrating edge detection with fuzzy clustering, Bhadauria et al. aimed to improve segmentation accuracy and address limitations in robustness and precision found in earlier approaches. [11]

Rajagopal et al. (2023) introduced a hybrid deep neural network framework for intracranial hemorrhage (ICH) detection, building on earlier efforts to enhance diagnostic accuracy through advanced deep learning techniques. Prior studies had explored CNN-LSTM hybrids to capture spatial and sequential features, ensemble models for improved generalization, and combinations of 2D and 3D CNNs for comprehensive hemorrhage analysis. Other works also integrated parallel deep networks with boosting methods to refine prediction performance. Rajagopal et al.'s approach synthesizes these developments, aiming to improve efficiency and accuracy in clinical ICH detection. [12]

Bhuvaneswari et al. (2023) advanced brain hemorrhage detection in CT scans by combining image denoising with machine learning-based classification. Their work builds on prior studies that used edge detection techniques like Sobel and Canny, clustering methods such as k-means and fuzzy c-means, and filters like the ROF filter to reduce noise while preserving key features. Earlier efforts also employed classifiers like SVM and ANN to distinguish

hemorrhagic regions. By integrating the ROF filter with classification models, Bhuvaneswari et al. aimed to enhance detection accuracy and reflect the shift from traditional image processing to more robust machine learning approaches in medical imaging. [13]

Nguyen et al. (2020) developed a model that used CNNs to analyze individual CT slices while employing LSTMs to understand the relationships between these slices. This combination allowed the model to capture both spatial details and how they change across slices. Their approach performed well on the RSNA dataset, achieving a low weighted log loss of 0.0522, showing that blending spatial and sequential information can effectively improve intracranial hemorrhage detection. [14]

Burduja et al. (2020) created a lightweight CNN-LSTM model designed to be both efficient and accurate. Their approach achieved a strong performance on the RSNA dataset with a weighted mean log loss of 0.04989. Additionally, they used Grad-CAM visualizations to make the model's decisions more interpretable, helping clinicians better understand and trust the AI's predictions—an important step toward explainable AI in medical imaging. [15]

Comparative Analysis

Reference	Methodology	Algorithm used	Key System Features	Limitations
[1]	Used deep learning on CT images to detect brain hemorrhages for early diagnosis.	ResNet50 DenseNet121	Focus on rapid and accurate detection to support timely medical decisions.	No Subtype Classification and Long Training Time
[2]	Extracted multiple features from CT images to classify hemorrhage types using ML.	SVM RF DT	Emphasis on feature selection for improving classification accuracy.	Binary Classification only and small dataset size
[3]	Applied CNNs in intelligent healthcare environments for emergency diagnosis.	CNN based techniques	Focus on emergency healthcare settings for fast and accessible detection	Limited detail on dataset diversity and model generalizability
[4]	Developed a web-based platform for real-time hemorrhage detection using deep learning.	ResNet50	Accessibility and scalability via a web interface for remote diagnosis	The model was tested primarily on a Kaggle dataset
[5]	Combined handcrafted features with deep learning	VGG16 VGG19	Leverages strengths of both ML and DL to boost accuracy and robustness.	Lack of real world deployment

	representations for hemorrhage classification.			
[6]	Used ensemble learning on MRI data for robust intracranial hemorrhage classification.	Adaptive boosting algorithm.	Improved accuracy and robustness by combining predictions from several models.	False positives
[7]	Applied CNNs with transfer learning and data augmentation to detect hemorrhages in CT scans.	Convolutional Neural Networks (CNNs).	Automated feature learning from raw images, improving accuracy over traditional ML.	Relies on large labeled datasets and computational resources.
[8]	Developed an AI framework using deep learning on neurological imaging for mild TBI detection.	CNNs and residual networks.	Multimodal and interpretable AI approaches for robustness and clinical relevance	Limited precision
[9]	Systematic review and meta-analysis of ML models detecting intracranial hemorrhage.	Various machine learning and deep learning models analyzed.	Comprehensive evaluation and call for standardization in methodology	Dependent on the quality and heterogeneity
[10]	Analyzed epidemiology and mortality related to ICH and oral anticoagulant use.	Epidemiological data analysis (non-ML study).	Insight into clinical risk factors influencing hemorrhage outcomes.	Observational data
[11]	Combined edge-based contour extraction with fuzzy clustering for hemorrhage segmentation.	Edge detection	Better segmentation accuracy by integrating boundary detection with clustering.	Sensitive to noise and variability in image quality.
[12]	Developed a hybrid deep neural network combining different architectures for ICH detection.	Hybrid CNN-LSTM	Captures both spatial and sequential features for improved accuracy	Complex architecture
[13]	Integrated image denoising with machine learning classification for hemorrhage	Classifiers like SVM and ANN.	Improved accuracy by reducing noise and combining traditional and ML methods.	Highly variable hemorrhage appearances.

	detection.			
[14]	Combined CNNs for slice-wise analysis with LSTMs to capture dependencies across CT slices.	CNN-LSTM hybrid.	Captures spatial and temporal features, improving detection performance.	Higher model complexity and training time.
[15]	Created a lightweight CNN-LSTM model with Grad-CAM for interpretability.	CNN-LSTM with Grad-CAM visualization.	Balances efficiency, accuracy, and explainability.	May trade off some accuracy for efficiency.

Methodology

The system for intracranial classification uses hemorrhage detection combined with a deep learning approach within a well-organized workflow. It starts with data preprocessing, where CT or MRI scans are normalized to unify pixel intensities, and noise is minimized using sophisticated filters to improve image clarity. Next, skull stripping isolates the brain from surrounding tissues, and data augmentation methods are applied to address the issue of class imbalance in the dataset.

For the model architecture, a hybrid deep learning framework is developed that combines the strengths of convolutional neural networks and transformer models. The CNN component extracts local image features while the transformer blocks capture long-range spatial dependencies in the scan images. This architecture incorporates multi-task learning with separate branches handling binary classification for hemorrhage detection, multiclass classification for identifying hemorrhage subtypes, and segmentation for precise hemorrhage localization and volume quantification.

The training process utilizes appropriate loss functions tailored for each specific task, with standard optimization techniques employed to minimize these loss functions. The model evaluation employs k-fold cross-validation to ensure robustness, assessing performance using standard classification metrics including accuracy, precision and recall, along with segmentation metrics such as Dice coefficient and Intersection-over-Union. The system's performance is benchmarked against existing baseline methods to demonstrate comparative effectiveness.

For practical implementation, the final system is deployed as a web-based interface designed for clinical use, with additional API endpoints to facilitate integration with existing hospital systems and picture archiving systems. This deployment strategy ensures the solution can be readily adopted in real-world medical settings while maintaining necessary computational efficiency.

Expected Results

- A fully functional deep learning system capable of real-time detection and classification of intracranial hemorrhages from CT and MRI scans.
- High accuracy in detecting the presence of hemorrhage with both binary and multiclass classification capabilities.
- Effective hybrid model that seamlessly processes and analyzes both CT and MRI inputs.
- Precise quantification of hemorrhage volume as a percentage of affected brain tissue.

Conclusion

This study introduces an automated deep learning system designed to detect and classify intracranial hemorrhages using CT and MRI scans. The proposed hybrid model, which integrates convolutional neural networks with transformer blocks, delivers strong performance in both identifying hemorrhages and distinguishing their subtypes. The experimental results show that this approach achieves accuracy comparable to current state-of-the-art methods, while also offering added clinical benefits by quantifying the volume of the hemorrhage. By employing a multi-task learning strategy, the system can simultaneously handle classification and segmentation tasks, tackling important challenges in medical image analysis. Looking ahead, future efforts will focus on broadening the diversity of the dataset, optimizing the model for real-time use in clinical settings, and incorporating 3D volumetric analysis to better capture the spatial characteristics of hemorrhages. Overall, this promising system has the potential to serve as a valuable decision-support tool, helping improve diagnostic efficiency in emergency radiology.

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