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A Survey on Detection of Intracranial Hemorrhage from CT Scan using Deep Learning

Dr. Soubhagyalakshmi P[1], L Shreyas Srinivas[2], Likhith K[3], S Manoj[4], Sharath Y[5]

Associate Professor, Dept. of Computer Science and Engineering, K. S. Institute of Technology, Bengaluru[1]

Student, Dept. of Computer Science and Engineering, K. S. Institute of Technology, Bengaluru[2]

Student, Dept. of Computer Science and Engineering, K. S. Institute of Technology, Bengaluru[3]

Student, Dept. of Computer Science and Engineering, K. S. Institute of Technology, Bengaluru[4]

Student, Dept. of Computer Science and Engineering, K. S. Institute of Technology, Bengaluru[5]

Abstract: Intracranial Hemorrhage (ICH) is a serious and potentially fatal condition marked by bleeding in the cranial cavity. It often arises from trauma, high blood pressure, or vascular issues. Early detection of ICH is crucial for improving patient outcomes and lowering mortality rates. Computed Tomography (CT) is the standard method for quickly diagnosing ICH due to its widespread availability and high sensitivity to acute bleeding. Despite this, radiologists must manually interpret CT images, which is labor-intensive and time-consuming, leading to variations in accuracy. Recently, deep learning, especially Convolutional Neural Networks (CNNs), has become a valuable tool for automating medical image analysis. This study looks at how deep learning techniques can automatically detect and classify ICH in brain CT scans. We review existing models, discuss data preprocessing methods, evaluate performance metrics, and highlight commonly used datasets like RSNA and CQ500. We also tackle challenges such as data imbalance, model interpretability, and clinical integration. Our findings show that deep learning models can achieve high diagnostic accuracy and significantly enhance clinical decision-making in emergency situations. Future research should aim to improve model generalization, explainability, and real-time deployment in clinical settings.

Keywords: Intracranial Hemorrhage, CT Scan, Deep Learning, Convolutional Neural Networks, Medical Image Analysis, ICH Detection, Automated Diagnosis, RSNA Dataset, CNN, Healthcare AI

I. INTRODUCTION

Intracranial Hemorrhage (ICH) is bleeding inside the skull, and it poses a life-threatening neurological emergency requiring prompt diagnosis and treatment. It can be caused by traumatic brain injury, aneurysms, high blood pressure, blood clotting disorders, or arteriovenous malformations. Depending on its location, ICH can be classified into types like epidural, subdural, subarachnoid, intraparenchymal, and intraventricular hemorrhages. Each type has unique clinical implications and treatment methods. Quickly and accurately identifying the type and extent of the hemorrhage is essential for guiding treatment decisions and preventing long-term neurological damage or death.

CT scans are the most common imaging method for detecting ICH due to their speed, accessibility, and ability to differentiate between blood and other brain tissues. However, analyzing CT scans manually is complex and time-consuming. It relies heavily on the radiologists' expertise. In busy clinical settings, delays in diagnosis or errors from fatigue and skill variability can hinder timely detection. This issue is particularly challenging in emergency and rural areas where access to expert radiologists is limited.

Recent advances in artificial intelligence (AI) and deep learning have changed medical image analysis. CNNs have shown outstanding results in tasks like image classification, object detection, and segmentation. Many studies have applied CNNs to automate ICH detection and classification in non-contrast CT brain scans. These models have demonstrated high sensitivity and specificity, often achieving performance levels comparable to experienced radiologists. They have the potential to assist with triage, cut down diagnostic delays, and enhance clinical outcomes.

This paper provides an in-depth study of how deep learning can help detect intracranial hemorrhage from CT scans. We explore various CNN architectures, compare publicly available datasets, discuss preprocessing methods, and evaluate model performance using standard metrics. We also address current limitations such as data imbalance, challenges with model interpretability and integration, and suggest future research paths to improve the reliability and clinical use of these AI solutions.

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II. LITERATURE SURVEY

1. This article [1] examines multiple deep learning models including CNNs and Residual Networks (ResNets) to detect different types of brain hemorrhages in non-contrast CT images. The researchers used the RSNA Intracranial Hemorrhage dataset. The model achieved high sensitivity across all hemorrhage types through slice-wise classification and attention-based models. While accurate, the system has drawbacks in generalization due to data imbalance and does not integrate with clinical metadata.

2. This article [2], published in Computerized Medical Imaging and Graphics, presents a 3D CNN model that processes volumetric CT data, capturing spatial features across adjacent slices. The model performed better than 2D models for subtype classification (e.g., epidural, subdural). However, it is expensive to compute and needs large annotated datasets for optimal performance, which limits its usefulness in low-resource clinical settings.

3. This article [3] proposes a hybrid CNN plus Transformer architecture that not only classifies ICH but also generates saliency maps for better understanding. The model incorporates radiological prior information and uses transfer learning to tackle data shortages. While it achieves high accuracy, the model's interpretability still depends on user expertise, and real-time use remains challenging due to high processing times.

4. This article [4] employs pre-trained CNNs like ResNet50 and InceptionV3 on the RSNA dataset and combines predictions using ensemble averaging. This approach significantly reduces training time and enhances generalization. Despite its high accuracy, the method lacks explainability and is limited to classification, without estimating hemorrhage volume.

5. This article [5] introduces a multi-view deep learning approach that analyzes CT slices from axial, coronal, and sagittal planes. The fusion of information improves detection of small bleeds and enhances subtype classification. However, multi-view training demands a lot of memory and extensive preprocessing, making it complicated to deploy in emergency scenarios.

III. OBJECTIVES

1. Automated Hemorrhage Detection: Create a solid deep learning system to automatically detect and classify different types of intracranial hemorrhages such as epidural, subdural, subarachnoid, intraparenchymal, and intraventricular from non-contrast CT brain scans.

2. Early and Accurate Diagnosis: Improve diagnostic accuracy and enable early detection by using CNNs and attention mechanisms to capture detailed features of hemorrhage, thereby supporting timely clinical decisions.

3. Generalization Across Diverse Datasets: Ensure the model’s robustness and ability to generalize by training and validating it on multiple diverse datasets with different acquisition protocols and demographics.

IV. METHODOLOGY

The proposed method includes several steps for the automatic detection and classification of intracranial hemorrhage (ICH) from CT scans using deep learning. The system efficiently processes DICOM or PNG image formats and provides accurate classification of hemorrhage types.

1. Data Collection and Preprocessing

Dataset: The RSNA Intracranial Hemorrhage Detection dataset is used, containing labeled CT slices for five types of hemorrhage: epidural, subdural, subarachnoid, intraventricular, and intraparenchymal.
Preprocessing: Convert DICOM images to 8-bit grayscale PNG.
Normalize pixel intensity and resize to 224×224 pixels.
Apply skull stripping (optional) and windowing techniques (brain, subdural, bone windows).
Data augmentation includes rotation, flipping, and contrast enhancement.

2. Model Architecture

Base Model: A pre-trained CNN like ResNet50, EfficientNet, or DenseNet serves as the feature extractor.
Custom Layers: Global Average Pooling, fully connected dense layers, and dropout layers for regularization.
Output Layer with Sigmoid or Softmax activation for multi-label classification.
Alternative Models: 3D CNN for volumetric data and hybrid CNN plus Transformer for spatial-temporal attention.

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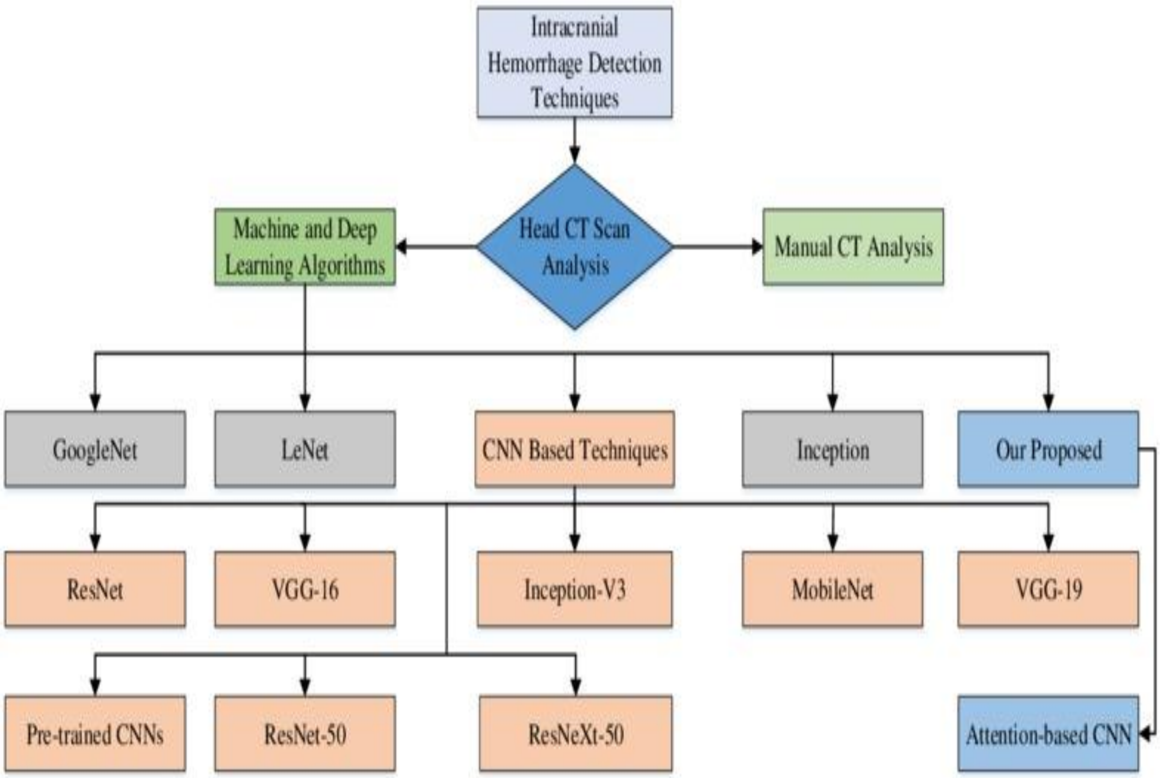

3. *Training Strategy*

Loss Function: Binary Cross Entropy or Focal Loss addresses class imbalance.
Optimizer: Adam or SGD with a learning rate scheduler.
Metrics: Accuracy, Precision, Recall, AUC-ROC.
Validation: Use stratified k-fold cross-validation to evaluate model generalization.

4. *Post-Processing and Explainability*

Utilize Grad-CAM or Integrated Gradients to create heatmaps showing hemorrhage regions.
Apply thresholding to refine detections.
Optional ensemble averaging of multiple models.

5. *Deployment*

Export the model using ONNX or TensorFlow Lite.
Integrate it into clinical systems for real-time CT scan analysis.
Create a UI/UX for radiologists to view results with explainable overlays

V. APPLICATION REQUIREMENTS

Hardware Requirements

1. Processor: Minimum Intel Core i3 (2.4 GHz) or AMD equivalent; recommended Intel Core i5/i7 or AMD Ryzen 5/7 for optimal performance.
2. RAM: Minimum 4 GB; recommended 8 to 16 GB for handling concurrent scraping, database operations, and UI rendering.
3. Storage: Minimum 250 GB HDD/SSD; recommended 500 GB SSD for faster data access and reduced latency in backend operations.
4. Display: Minimum 1366x768 resolution; recommended Full HD (1920x1080) for better visibility of web interface and debugging tools.
5. Internet Connectivity: Minimum 10 Mbps for basic scraping tasks; recommended 50 Mbps or higher for smooth operation during bulk data extraction.

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6. Graphics Card: Not mandatory; optional GPU (NVIDIA or AMD) if integrating ML models for future improvements.
7. Power Backup: A UPS is recommended for desktop setups to prevent data loss during scraping or update cycles.
8. Peripheral Devices: Standard keyboard and mouse; optional dual-monitor setup for better developer efficiency.

Software Requirements

1. Operating System: Compatible with Windows 10/11, Ubuntu 20.04 or later (Linux is recommended for server deployment), or macOS 10.14 or later.

2. Programming Language: Python 3.8 or higher for scripting web scraping and preprocessing modules.

3. *Python Libraries:*
- BeautifulSoup for static HTML parsing
- Selenium for handling dynamic content
- pandas and NumPy for data manipulation
- requests and urllib for HTTP operations
- regex and lxml for pattern matching and XML parsing.

4. *Backend Framework*:
- Node.js (v14 or later) with Express.js for API handling
- Or Django (v3.2 or later) for an integrated backend and admin interface.

5. *Frontend Framework:* React.js (v17 or later) for building responsive and dynamic user interfaces.
6. *Database System:* MongoDB for storing semi-structured expert profiles with support for schema flexibility and index-based querying.

7. *Scheduling Tools*: Cron jobs or Task Scheduler for periodic scraping, auto-refresh, and scheduled database updates.

8. *Security Tools:* HTTPS for secure communication; Helmet.js or Django-secure for HTTP header protection; input sanitization modules.

9. *Development Tools:*
- Visual Studio Code or PyCharm as IDEs
- Git for version control
- Mail carrier for API testing
- ChromeDriver or GeckoDriver for Selenium browser automation.

10. *Optional Tools:*
- Docker for containerized deployment
- Anaconda or venv for environment isolation
- Webpack or Babel for frontend build optimization.

VI. CONCLUSION

Detecting intracranial brain hemorrhage from CT scans is a critical task in emergency medicine that needs both speed and accuracy. Traditional manual diagnosis by radiologists can be effective, but it is time-consuming and prone to human error, especially under heavy workloads. Deep learning has become a valuable tool to help with clinical diagnosis by automating the detection and classification of different types of hemorrhages.

This study presents a deep learning-based approach for accurately identifying intracranial hemorrhages using convolutional neural networks and advanced architectures like 3D CNNs and attention mechanisms. The method includes important stages such as preprocessing, model training, classification, and explainability using techniques like Grad-CAM. This provides high accuracy along with a visual understanding of the model’s predictions.

Using large-scale annotated datasets like the RSNA ICH dataset shows strong potential for clinical deployment. Moreover, this is especially important in emergency settings where quick intervention is crucial. However, challenges like data imbalance, the need for real-time processing, and generalization across different patient groups must still be tackled.

Future work may involve integrating multimodal data, improving explainability frameworks, and deploying the system in hospital PACS. Overall, using deep learning for intracranial hemorrhage detection represents a significant step toward more intelligent and efficient neuroimaging diagnostics.

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