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Brain Hemorrhage Detection

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***Abstract*— Brain hemorrhages are life-threatening medical conditions that require immediate and accurate diagnosis to prevent severe neurological damage or death. Timely and accurate diagnosis of brain hemorrhages is crucial for preventing serious medical complications and improving patient outcomes. This study presents an autonomous diagnostic methodology employing neural networks for ICH identification and classification. A deep learning framework utilizing an optimized DenseNet-121 model is implemented to examine brain CT scans and detect different categories of intracranial bleeding. The system aims to address limitations of traditional manual diagnosis, such as time constraints, limited availability of radiologists, and human error. A robust preprocessing pipeline ensures data consistency, while the model integrates attention mechanisms and optimized thresh- olds to improve interpretability and classification accuracy. By streamlining the diagnostic workflow, this AI-assisted method supports faster decision-making and more efficient resource utilization in clinical settings. The results highlight the growing role of artificial intelligence in enhancing medical diagnostics and offer a promising solution for improving the speed and reliability of brain injury assessment.**

***Index Terms*— Brain Hemorrhage Detection, Convolutional Neural Networks (CNN), DenseNet-121, Deep Learning, Medical Imaging, CT Scan Analysis, Automated Diagnosis, Attention Mechanism.**

I. INTRODUCTION

Brain hemorrhages are serious medical emergencies involving vascular rupture within cranial tissue, potentially resulting in elevated pressure inside the skull, brain compression, and irreversible damage if not treated promptly. Early and accurate detection is vital to improve outcomes and reduce mortality. Manual interpretation of CT scans is not only time-consuming but also limited by inter-radiologist variability, leading to inconsistent diagnoses and delayed treatments. [4] The human brain is susceptible to various types of hemorrhage depending on the location of bleeding, including subarachnoid, subdural, epidural, intraparenchymal, and intraventricular hemorrhages, each with distinct visual features on CT imaging that require expert-level discrimination[7] Recent studies reinforce the urgent need for intelligent diagnostic support. Classifying hemorrhages accurately remains difficult due to low contrast and complex lesion appearances in CT images, which demand intelligent feature learning strategies. [5] Intracranial hemorrhage (ICH) accounts for a significant portion of global stroke-related mortality and demands rapid diagnosis due to its life-threatening nature and high rate of complications if untreated. [8] To address these challenges, recent models incorporate attention mechanisms and generative adversarial networks to improve focus on critical regions and balance class distribution, significantly enhancing hemorrhage subtype classification accuracy.

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[8] Furthermore, the use of supervised methods and segmentation-guided attention has enabled models to learn more diagnostically relevant features even from noisy labels, reducing dependency on expensive manual annotations. [5] In summary, advancements in deep learning and imaging-based classification continue to revolutionize the diagnostic pipeline for brain hemorrhages, supporting the transition to faster, more interpretable, and more scalable healthcare solutions [9]. This research investigates the application of machine learning algorithms, specifically deep neural architectures, to enable automated identification of cerebral bleeding. CNNs excel at analyzing medical images, identifying subtle patterns such as tissue density changes and hemorrhage locations with high accuracy. By automating diagnosis, the system can rapidly classify hemorrhage types, reduce the workload on healthcare professionals, and improve treatment speed and accuracy. Incorporating these insights, our work builds upon DenseNet121 with an attention mechanism, optimal thresholding, and interpretability tools to deliver fast, accurate, and explainable classification of brain hemorrhage subtypes

The paper is divided into several sections:

Section II provides a brief overview of previous research work on the topic. Section III presents the proposed methodology. Section IV depicts the implementation and testing results and finally, Section V concludes the paper.

II. Literature Review

Brain hemorrhage detection and classification are critical areas of medical research, as prompt and precise diagnosis is vital for improving patient outcomes. Intracranial hemorrhage (ICH) is a life-threatening condition with mortality rates reaching up to 60% within 30 days if incorrectly diagnosed, making rapid and precise detection essential [1]. Advances in deep learning, especially convolutional neural networks (CNNs), have enabled significant progress in this field due to their ability to analyze and classify complex medical imaging data[1] [2] [3]. Automated systems utilizing CNNs can reduce radiologists' diagnostic workloads, provide second opinions, and detect subtle abnormalities that may be missed during manual analysis [6] [10] [11]. Recent comprehensive meta-analyses have demonstrated the robust performance of deep learning models in ICH detection [15]. These findings underscore the potential of AI systems to serve as effective triage tools in emergency settings, though performance variability across different ICH subtypes and populations remains a consideration [15]. The five primary subtypes of ICH – epidural (EDH), sub- dural (SDH), intraparenchymal (IPH), intraventricular (IVH), and subarachnoid (SAH) hemorrhages – each present unique diagnostic challenges that have been addressed through various deep learning approaches [2] [3] [4] [7] [8]. This study focuses on the RSNA Intracranial Hemorrhage Detection dataset, a comprehensive collection of head CT scans curated by the Radiological Society of North America. Preprocessing plays a pivotal role in preparing CT scan images for model training and testing. The preprocessing pipeline involves extracting relevant data through windowing techniques, applying Hounsfield unit (HU) conversions, and converting grayscale images to RGB format using three-channel grayscale duplication [1] [2] [6]. Following this, images are normalized, standardized, and resized to dimensions suitable for deep learning models. The approach of applying specific windowing techniques, such as brain, blood, and bone windows, aligns with methodologies demonstrated in prior research for capturing critical features across varying HU ranges [1] [2] [6]. Advanced preprocessing incorporating anisotropic filtering and specialized windowing has shown to improve model performance significantly [1]. Various CNN architectures have been extensively evaluated for ICH detection and classification. Early studies using custom CNN models and modified VGG16 architectures demonstrated promising results, with VGG16 achieving 96.8% accuracy un- der slice-randomized conditions, though performance dropped significantly to 70.7% under subject-randomized conditions, highlighting the importance of proper validation methodology[1] [7]. Comparative studies have shown that ResNet50, EfficientNet, MobileNet, DenseNet, and Xception models achieve varying levels of accuracy, with EfficientNet and MobileNet both reaching 88% accuracy in some implementations [4] [6] [7]. More sophisticated approaches incorporating CNN-LSTM hybrid models have demonstrated enhanced performance, with one study achieving 98.1% accuracy and 0.982 AUC through the integration of spatial and temporal features [2]. Advanced architectural innovations have emerged to address specific challenges in ICH detection. Attention-based mechanisms have been incorporated to focus on diagnostically relevant regions while suppressing noise and irrelevant features [5][8] [11]. Weakly supervised learning approaches utilizing segmentation guidance have achieved remarkable results, with one study reporting 98.1% accuracy and 74.6% F1-score on nearly 80,000 CT images [5]. Hybrid attention-based ResNet architectures combined with primary component analysis for dimensionality reduction and deep convolutional generative adversarial networks (DCGAN) for addressing class imbalance have achieved exceptional subtype-specific accuracies: 99.2% for EDH, 97.1% for IPH, 96.7% for IVH, 96.7% for SDH,and 96.1% for SAH [8]. The clinical validation of deep learning models has demonstrated significant potential for real- world implementation. Furthermore, state-of-the-art winning solutions from the RSNA challenge have demonstrated exceptional performance with hybrid models combining 2D CNNs and recurrent neural networks, achieving AUCs exceeding0.98 for most ICH subtypes while maintaining generalizability across multiple institutions and scanner types [3]. Emerging technologies and methodologies continue to expand the scope of ICH detection beyond traditional CT imaging. Electrical impedance tomography represents an innovative approach for brain disease detection, with novel classification methods based on electrode arrangement achieving accuracies higher than 0.9 and specificity reaching 1.0 when incorporating residual networks [9]. Additionally, comprehensive volume analysis algorithms have been developed alongside classification systems, enabling quantitative assessment of hemorrhage burden with reported volume estimations of 1,035.91mm³ and9.25cm³ [10]. The integration of Health4.0 applications and digital twin technology further enhances the potential for real- time monitoring and treatment optimization [8]. Despite these advances, several challenges persist in the field of automated ICH detection. Data imbalance remains a significant issue, particularly for rare subtypes like epidural hemorrhage and irregular subarachnoid hemorrhage shapes [13]. The need for interpretability in model predictions continues to drive research toward attention-based architectures and weakly supervised learning approaches [4] [5] [11]. Ethical considerations regarding patient data use and the requirement for prospective real-world validation studies remain paramount [15]. Additionally, the performance variability across different commercial tools, with sensitivity ranges from 68–98% for systems like Aidoc, emphasizes the need for standardized evaluation protocols and continuous model refinement [15]. The integration of advanced augmentation techniques, sophisticated preprocessing pipelines, and ensemble learning methods represents the current frontier in achieving robust, clinically deployable ICH detection systems that can effectively assist healthcare providers in emergency settings while maintaining high accuracy and reliability across diverse patient populations

TABLE I. SUMMARY OF LITERATURE REVIEW

Ref	Dataset	Dataset Type	Model/Architecture	Learning Approach	Hemorrhage Subtypes Considered	Accuracy
[4]	RSNA Brain CT Dataset	Labelled	Xception,DenseNet121, CNN	Transfer Learning	Subdural, Epidural, Intraparenchymal, Intraventricular, Subarachnoid	Up to 96.7%
[5]	RSNA ICH Dataset	Labelled	WsGSA (Weakly-supervised CNN)	Deep Learning + Weak Supervision	Subdural, Epidural, Intraparenchymal, Intraventricular, Subarachnoid	98.1%
[7]	Private RSNA CT Dataset	Labelled	VGG16, ResNet50, Xception	Deep Learning	Subdural, Epidural, Intraparenchymal, Intraventricular, Subarachnoid	Up to 96%
[8]	RSNA ICH Detection 2019	Labelled	ResNet-152V2 + PCA + Attention + DCGAN	Deep Learning + GAN + PCA	Subdural, Epidural, Intraparenchymal, Intraventricular, Subarachnoid	99.2%(EH), 96.1–97.1% (others)
[9]	Simulated EIT Datasets	Labelled	Residual Network with Prior Info	Deep Learning	Not based on subtypes. Classified by location: Frontal, Temporal/Parietal, Occipital lobes	>90%

III. PROPOSED METHODOLOGY

A. System Overview

The proposed system is a Convolutional Neural Network (CNN)-based automated diagnostic application aimed at detecting and classifying brain hemorrhages using CT scan images. The system processes grayscale DICOM images, converts them into a compatible RGB format through specialized windowing techniques, and feeds them into a fine- tuned DenseNet121 CNN model enhanced with an attention mechanism. The classification targets five specific types of hemorrhages: epidural, subdural, subarachnoid, intraparenchymal, and intraventricular. Preprocessing techniques such as normalization, data augmentation, and segmentation are employed to improve model robustness and ensure high diagnostic accuracy. The objective is to assist radiologists with an intelligent support tool that minimizes diagnostic delays and improves the efficiency and precision of medical decision-making.

B. Tools and Technologies

The system is developed using Python 3.x as the primary programming language, chosen for its flexibility and extensive support in machine learning and image processing. Essential libraries include TensorFlow/PyTorch for deep learning frame- works used in CNN model development and training, NumPy and pandas for numerical operations and metadata management, scikit-image and PIL (Pillow) for image preprocessing and transformation, and Matplotlib/Seaborn for visualization of model performance and data analysis. Medical imaging tools comprise pydicom for reading and manipulating DICOM images and Hounsfield windowing functions for contrast enhancement. The hardware requirements include 16 GB+ RAM and 1TB storage for training efficiency.

C. System Architecture

The system architecture begins with data acquisition of CT scans collected from a subset of the RSNA Intracranial Hemorrhage Detection dataset containing 10000 CT scan images in DICOM format. The preprocessing pipeline involves DICOM loading and grayscale image extraction, followed by Hounsfield unit normalization and windowing for brain, blood, and bone characteristics. Images are then converted to RGB format using windowed channels and resized to 224x224 pixels with augmentation techniques applied. Preprocessed RGB images act as feeding data to the neural network model based on DenseNet-121 architecture. The classification targets six specific types of hemorrhages: no hemorrhage, epidural, subdural, subarachnoid, intraparenchymal, and intraventricular. The system evaluation and feedback mechanism utilizes accuracy, precision, recall(sensitivity), F1-score, and confusion matrix metrics to assess model performance.

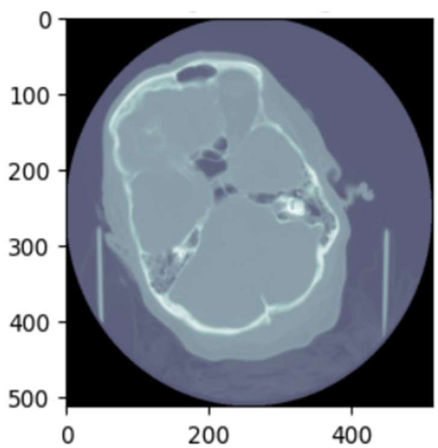

Fig. 1. Image of brain before preprocessing

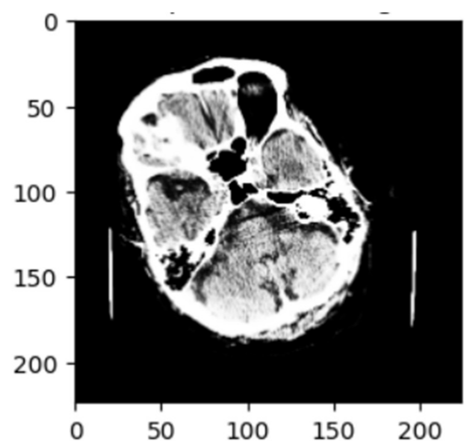

Fig. 2. Image of brain after preprocessing

D. Model Architecture

The model architecture utilizes the DenseNet121 model pretrained on the ImageNet dataset as the base feature extractor, with the original classification layer removed to allow custom output design suited for medical imaging tasks. A strategic layer freezing approach is employed where initial layers of DenseNet121 are frozen while the final 75 layers are unfrozen to enable fine-tuning on medical imaging data. The characteristic extraction workflow integrates a Global Average Pooling (GAP) component to diminish dimensional complexity and capture significant attributes, followed by Batch Normalization applied post- GAP to stabilize and accelerate training convergence. Two dense layers are implemented: a first block with 512 units and a second block with 256 units, both followed by Batch Normalization, ReLU activation, and Dropout for regularization. An attention mechanism component improves the framework's concentration on essential characteristics by applying dense layers with tanh and sigmoid activations, with the resulting attention weights element-wise multiplied with the second dense block output. The output layer consists of a sigmoid-activated dense layer for multi-label classification, incorporating L2 regularization to mitigate overfitting. The training configuration employs the Adam optimizer with gradient clipping to prevent exploding gradients, custom
focal loss function to address class imbalance common in medical datasets, and evaluation metrics including Accuracy, Precision, Recall(sensitivity), and Area Under Curve (AUC) for comprehensive performance assessment.

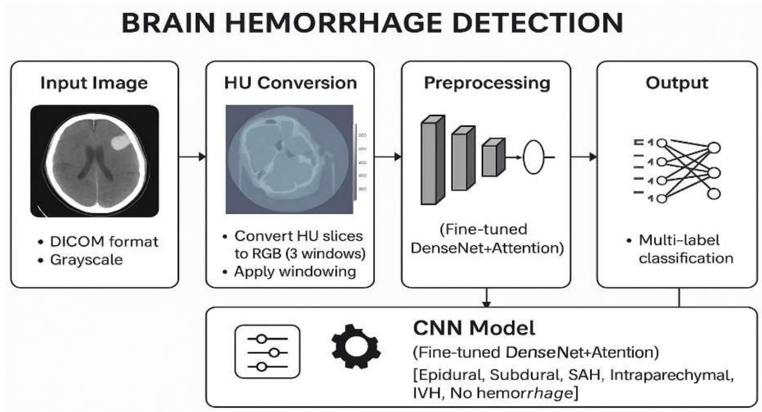

Fig. 3. Flow Diagram

D. Implementation

The complete workflow is segmented into six sequential phases as demonstrated in the system architecture:
Step 1: CT scan images from the RSNA dataset are loaded in DICOM format. The images contain various types of hemorrhages: epidural, subdural, subarachnoid, intraparenchymal, and intraventricular.
Step 2: DICOM images undergo preprocessing including Hounsfield unit normalization, windowing techniques, and conversion from grayscale to RGB format. Input images undergo resizing to 224×224 pixel dimensions and pixel value scaling to the 0-1 interval.
Step 3: Preprocessed images are fed into the fine-tuned DenseNet121 model with an attention mechanism. The model generates probability predictions for each of the six classes using sigmoid activation.
Step 4: Optimal thresholds are computed for each class using Precision-Recall curves to convert probability outputs into binary classifications. Thresholds are bounded within the [0.1, 0.9] range.
Step 5: The model outputs classification results identifying the type of hemorrhage present. Error analysis is performed to detect false positives and false negatives with detailed CSV reporting.
Step 6: The evaluation framework incorporates accuracy, precision, recall, F1-score, and AUC measurements. Outcomes are displayed using ROC plots and confusion matrices, subsequently preserved for medical implementation.

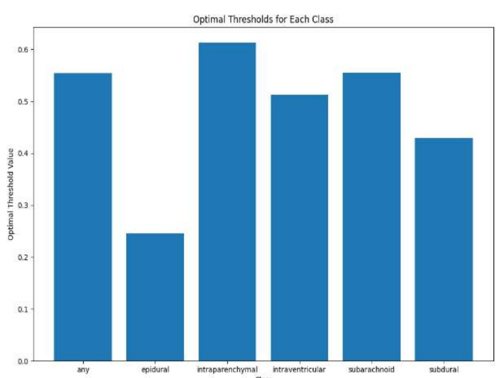

Fig. 4. Optimal Thresholds for each class

IV. RESULTS

A. Dataset Evaluation Setup

The proposed model was evaluated on a test dataset comprising 2,000 brain CT images. The evaluation encompassed classification for detecting five specific types of intracranial hemorrhage: epidural, intraparenchymal, intraventricular, subarachnoid, and subdural, along with a binary classification for detecting any hemorrhage presence. Optimal decision thresh- olds were determined using precision-recall curve analysis to maximize F1-scores for each hemorrhage type.

B. Overall Performane Analysis

The model's total accuracy for all hemorrhage classes was 93.83%. Precision, recall, and F1-score were 0.396, 0.480, and 0.373 for the macro-averaged measures, and 0.308, 0.472, and 0.372 for the micro-averaged metrics. After correcting for class imbalance, the weighted averaged metrics showed an F1-score of 0.441, precision of 0.472, and recall of 0.472. The model obtained an accuracy of 0.873, precision of 0.526, recall of 0.697, F1-score of 0.600, and AUC of 0.890 for the crucial task of recognizing the presence of any hemorrhage This result shows how well the model can screen for general hemorrhages. Its high sensitivity (recall) is especially useful for clinical applications where failing to detect a hemorrhage could have serious repercussions.

C. Hemorrhage Type-Specific Performance

The best performance was demonstrated by Intraventricular hemorrhage, which had an accuracy of 0.969, AUC of 0.937, precision of 0.520, recall of 0.591, and F1-score of 0.553.

Intraparenchymal hemorrhage produced an F1-score of 0.504 and an AUC of 0.921 with excellent accuracy (0.965) and precision (0.783) but low recall (0.371). This demonstrates the model's cautious approach to forecasting this sort of hemorrhage, giving precision precedence over sensitivity. Subdural hemorrhage showed balanced performance with a recall of 0.540, F1-score of 0.424, accuracy of 0.908, precision of 0.349, and AUC of 0.865. Given the balanced precision- recall trade-off, this indicates a reasonable level of clinical value. Moderate performance was demonstrated by Subarachnoid hemorrhage, with accuracy of 0.931, precision of 0.308, recall 0.398, F1-score of 0.347, and AUC of 0.832. Although a fair discriminative power is suggested by the AUC, the lesser precision shows difficulties in lowering false positive predictions for this type of bleeding. Epidural hemorrhage presented the most challenging classification with accuracy of 0.921, extremely low precision 0.019despite moderate recall 0.500, resulting in an F1-score of 0.036and AUC of 0.865. This reflects the extreme rarity of epidural cases in the dataset and the model's tendency to generate false positives for this class, highlighting the challenges of machine learning with severely imbalanced datasets.

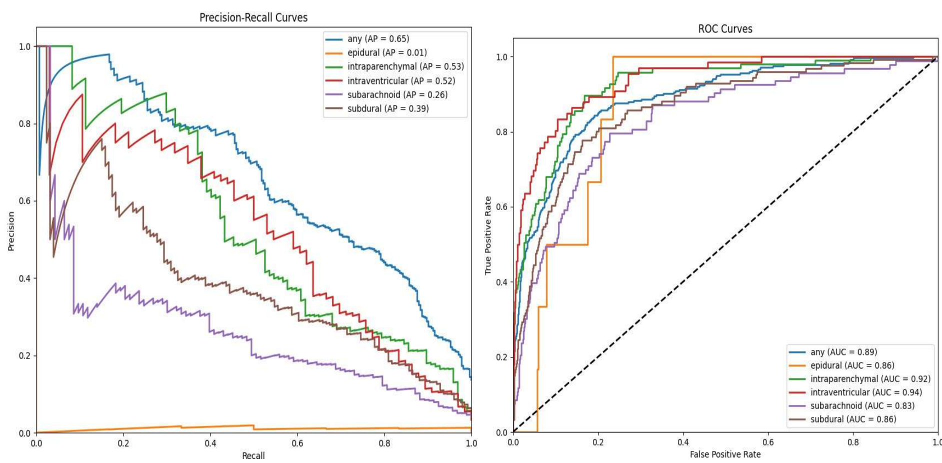

Fig. 5. Precision-Recall Curves (left) and ROC Curves (right) for all hemorrhage types. The curves demonstrate strong discriminative performance with AUC values ranging from 0.83 to 0.94. Intraventricular hemorrhage achieved the highest AUC (0.94), while epidural hemorrhage showed the lowest average precision (0.01) due to extreme class imbalance.

D. Error Analysis

The model generated 172 false positives (8.60% of total images) and 83 false negatives (4.15% of total images). False positive cases primarily involved misclassification of normal scans as having hemorrhage, with common erroneous predictions including subdural and epidural hemorrhages. Notable false positive examples include ID_028f2ac1d and ID_01e95e7d7. False negative cases represented missed hemorrhages, particularly challenging multi-type cases. Critical missed cases include ID_0081aa50d and ID_02da8c2f4.

E. Discussion and Clinical Implementations

The ROC curves demonstrate strong discriminative performance across all hemorrhage types, with AUC values ranging from 0.83 to 0.94. The precision-recall curves reveal important trade-offs between precision and recall. The results indicate that while the model demonstrates strong overall performance for hemorrhage detection, significant class imbalance challenges persist, particularly for rare hemorrhage types such as epidural. The high

AUC values across all classes sug- gest effective feature learning, though precision-recall trade- offs vary considerably between hemorrhage types, reflecting the inherent difficulty in distinguishing subtle radiological features in CT imaging. From a clinical perspective, the model's high sensitivity for detecting any hemorrhage (recall = 0.697) is promising for screening applications, while the varying precision across specific hemorrhage types suggests the need for radiologist oversight in differential diagnosis. The accuracy values ranging from 0.873 to 0.969 across different hemorrhage types demonstrate the model's overall reliability, though the extreme variation in support underscores the need for larger, more balanced datasets for rare hemorrhage types.

V. CONCLUSION

This Brain Hemorrhage Detection initiative illustrates ma- chine learning's capacity to transform medical imaging and di- agnostic practices. By tackling the crucial problem of correctly recognizing brain hemorrhages from CT scans, this system addresses a potentially fatal illness that requires immediate and accurate intervention. The creation of an automated system aids in quick decision-making and reduces the workload of radiologists.

This approach begins with data collection and preprocessing, followed by training a fine-tuned DenseNet121 CNN model with an integrated attention mechanism. The structured training and saving module further enhances the system's re- producibility, stability, and deployment readiness. Techniques such as model checkpointing, early stopping, and learning rate adjustment ensure efficient and robust learning, while the saved model supports consistent deployment in real-world clinical environments.

Overall, the integration of deep learning for automated hemorrhage classification improves diagnostic accuracy, speeds up decision-making, and supports resource optimization. The project highlights the potential of artificial intelligence to save lives, modernize healthcare delivery, and serve as a reference model for future applications in medical diagnostics.

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