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Deep Learning Approaches for the Classification of Intracranial Haemorrhage

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ABSTRACT: Brain hemorrhages are characterized by the rupture in the arteries of brain due blood clotting or high blood pressure (BP), presents a significant risk of traumatic injury or even death. This bleeding results in the damage in brain cells, with common causes including brain tumors, aneurysm, blood vessel abnormalities, amyloid angiopathy, trauma, high BP, and bleeding disorders. When a hemorrhage happens, oxygen can no longer reach the brain tissues and brain cells begin to die if they are depleted of oxygen and nutrients for longer than three or four minutes. The affected nerve cells and the related functions they control are damaged as well. Early detection of brain hemorrhages is crucial. In this paper an efficient hybrid deep learning (DL) model is proposed for the intracranial hemorrhage detection (ICH) from brain CT images. The proposed method integrates DenseNet 121 and Long Short-Term Memory (LSTM) models for the accurate classification of ICH. The DenseNet 121 model act as the feature extraction model. The experimental results demonstrated that the model attained 97.50% accuracy, 97.00% precision, 95.99% recall and 96.33% F1 score, demonstrating its effectiveness in accurately identifying and classifying ICH.

KEYWORDS: Intracranial hemorrhage; deep learning; DenseNet 121; LSTM; brain CT images

I. INTRODUCTION

Hemorrhage describes the occurrence of bleeding either internally or externally from the body. A sudden blood clot in arteries can cause brain hemorrhage, which can lead to symptoms such as tingling, palsy, weakness, and numbness. Recognizing these symptoms is crucial for initiating immediate treatment. Brain hemorrhages occur when a blood vessel in the brain leaks or bursts, results in hemorrhagic stroke. ICH is a life-threatening neurological condition that can occur due to various causes, such as increased BP, hemorrhage secondary to infarct, trauma, tumor hemorrhage, and more [1]. One of the most common causes of ICH is traumatic brain injury. When blood pools within the brain parenchyma, it forms a hematoma, which increases pressure on the surrounding brain tissues. This pressure leads to reduced blood flow and ultimately kills brain cells.

There are various forms of hemorrhages, each occurring in different areas of the skull. Epidural hemorrhage (EPD) occurs when there is damage to both the skull and the dura mater, leading to bleeding. An accumulation of blood within the brain's tissues causes an intraparenchymal hemorrhage (ITP), also, the bleeding in the brain's ventricular system is known as intraventricular hemorrhage (ITV). Subdural hemorrhage refers to a collection of blood within the subdural spaces, which are potential spaces between the dura and arachnoid of the meninges surrounding the brain. Subarachnoid hemorrhage is an extra-axial intracranial hemorrhage located within the subarachnoid spaces [2].

Diagnosing a brain hemorrhage is challenging because some individuals do not exhibit any physical signs. Computed tomography (CT) is the prime method used for the diagnosis of ICH. During a CT scan, a set of images is generated using X-ray beams, capturing the various intensities of brain cells from their X-ray absorbency levels [3]. The regions of ICH are depicted as hyperdense areas without a defined architecture. Radiologists analyze these scanned images and confirm the presence, type and location of ICH. However, the accuracy of the diagnosis depends on the accessibility and experience of the radiologist, which can lead to ineffective and impressive results [4].

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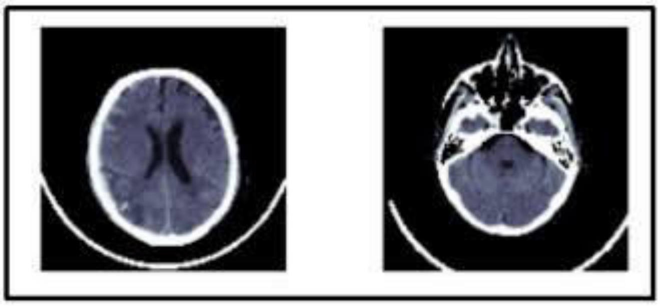

Fig 1: Toward the detection of intracranial hemorrhage

In recent years, artificial intelligence (AI), particularly DL, has significantly transformed image analysis, becoming an essential tool in medical diagnostics. This study employs a new hybrid DL approach to detect and classify ICH from brain CT images. This approach combines the strengths of Advanced Neural Network (ANN) such as DenseNet 121 and LSTM to increase the accuracy and reliability of hemorrhage detection. The performances of the model are assessed using the metrics of precision, accuracy, recall, and F1 score, demonstrating its effectiveness in identifying brain hemorrhages.

II. RELATED WORKS

Using three CNN models—LeNet, GoogLeNet, and Inception-ResNet—Phong et al. (2017) proposed a deep learning-based technique for detecting brain hemorrhage. Using preprocessing and augmentation techniques like rotation and brightness correction, the study examined 100 CT cases from the 115 Hospital in Ho Chi Minh City. The findings demonstrated the high accuracy of the classifiers: LeNet achieved 99.7%, GoogLeNet achieved 98.2%, and Inception-ResNet achieved 99.2%. All of the models demonstrated that they could be helpful in the clinic for detecting brain hemorrhages, despite LeNet taking longer to train.

Yao et al. (2020) stressed how important it is to identify bleeding as soon as possible after traumatic brain injury (TBI). Radiologists painstakingly annotated 185 training, 67 validation, and 77 testing CT scans for their study. To reduce the need for manual review and expedite the decision-making process, we developed automated detection models. The system's performance was on par with that of expert radiologists, highlighting the therapeutic value of AI methods in emergency care. In order to detect cerebral bleeding from CT slices.

Cortés-Ferre et al. (2023) combined the ResNet and EfficientDet architectures with a visual explanation system (Grad-CAM). Using the RSNA Kaggle dataset, which contains over 750,000 photos, their model achieved 92.7% accuracy and a ROC AUC of 0.978. Strong performance was confirmed by clinical validation, and Grad-CAM clarified the results by highlighting key areas for prediction-making. The potential of explainable AI for healthcare decision support was demonstrated by this study.

In order to identify bleeding, Malik et al. (2024) looked at a number of deep learning models, including ResNet50, SEResNeXt, EfficientNetB2, and ResNeXt. With a validation accuracy of 93.29% and a training accuracy of 99.95%, EfficientNetB3 performed best. Prior to using transfer learning, they employed preprocessing methods like scaling, normalization, and augmentation. In addition to discussing future strategies like real-time applications and multimodal data fusion, the paper concentrated on EfficientNetB3's ability to balance accuracy and computing efficiency. The studies show that deep learning has made great strides in the identification and categorization of brain hemorrhages using CT imaging. It has been demonstrated that models such as LeNet, ResNet, EfficientNet, and hybrid approaches are highly accurate and dependable.

They frequently outperform skilled radiologists. However, most previous research has focused on binary classification of hemorrhage occurrence or used limited datasets, suggesting room for improvement in multiclass classification of particular bleeding subtypes. In order to close this gap, this study performs Five-class classification using the ResNet and DenseNet121 architectures, which includes five different types of hemorrhage. This provides a more comprehensive and therapeutically beneficial solution.

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III. METHODOLOGY

The methodology of this research focuses on developing a deep learning–based system for the detection and classification of intracranial hemorrhage (ICH) from computed tomography (CT) scans. The RSNA Intracranial Hemorrhage Detection challenge, which offers a sizable collection of brain CT scans labeled for various hemorrhage types, provided the dataset used in this investigation. Five categories of hemorrhage subtypes— epidural, intraparenchymal, intraventricular, subarachnoid, and subdural—were established. The entire process is divided into sequential stages: data acquisition, preprocessing, model design, training, and evaluation.

Preprocessing is an important step in getting CT scan pictures ready for deep learning model training. Raw medical photos often have noise, artifacts, and changes in intensity, so they went through several procedures to make sure they were consistent, of good quality, and suitable for model input. First, Hounsfield Units (HU) were used to turn all DICOM pictures into pixel values. HU is a common scale for interpreting CT scans. This step makes sure that tissue density is shown correctly on all scans. Three clinical windows were used to improve diagnostic features: the brain window (WL=40, WW=80), the bone window (WL=300, WW=1500), and the subdural window (WL=80, WW=200).

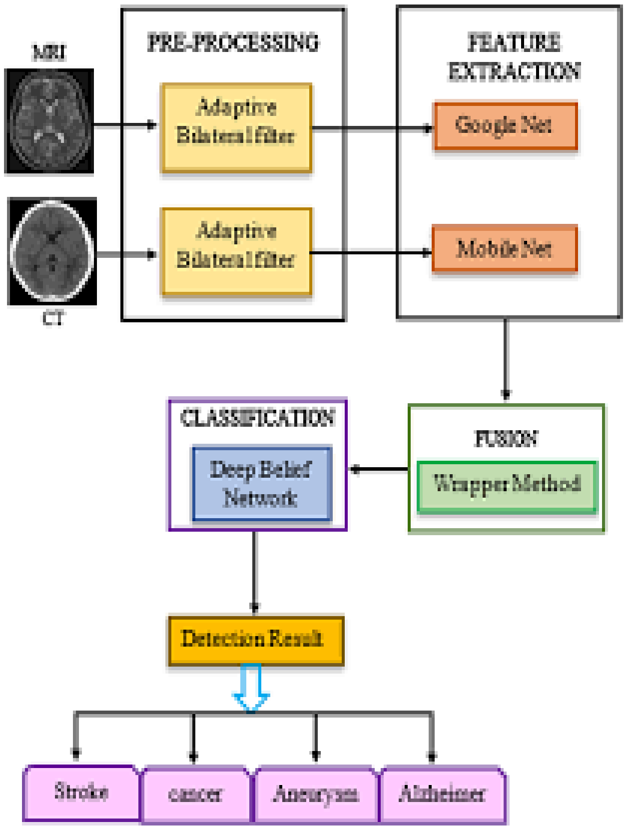

Fig 2: Classification of brain disease using deep learning with multi-modality images

I averaged the outputs of these windows to generate a multi-channel depiction that made both soft tissue and bleeding areas easier to see.Next, the photos were cropped in the center and zoomed in on the most important parts of the brain, cutting down on background noise. After this, all of the photos were downsized to 512 × 512 pixels, which made sure that the dataset was consistent and worked with deep learning architectures. I used data augmentation techniques including rotation, flipping, brightness adjustment, and scaling to make the model more versatile and less likely to overfit. These changes make the models learn more robust features by mimicking real world changes in CT images. Finally, the dataset was normalized and turned into three-channel PNG pictures, which work directly with CNN-based models like ResNet and DenseNet.

Since ResNet18 and DenseNet121 have varying strengths in feature extraction and efficient gradient propagation, they were both selected for the classification of five different types of brain hemorrhages: epidural, intraparenchymal,

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intraventricular, subarachnoid, and subdural. The Residual Network family includes ResNet18. It makes use of residual blocks, which enable shortcut connections to allow inputs to bypass convolutional layers. This allows learning to remain stable even in deeper networks by resolving the vanishing gradient issue. Its convolutional backbone consists of 18 layers arranged into four residual stages. A fully connected layer with six neurons—one for each type of bleeding—and adaptive average pooling follow. Conversely, DenseNet121 employs dense connectivity, meaning that every layer receives feature mappings from every layer that comes before it. Both low-level and high-level patterns are captured, and feature reuse is encouraged. There are four dense blocks with transition layers in between each of the 121 layers that make up the DenseNet121 backbone. A fully connected layer with six output neurons follows, followed by global average pooling. Since a single CT scan can reveal multiple types of hemorrhage, both networks employ sigmoid activation to compute independent probabilities for each class, enabling multi-label classification. This combination of topologies enables the study to swiftly and precisely identify minute patterns in CT scans using both residual and densely connected designs.

Five types of brain hemorrhages—epidural, intraparenchymal, intraventricular, subarachnoid, and subdural—were categorized using ResNet18. This is due to its proficiency in capturing particular image data and training deep networks. In order to utilize pretrained weights, the model makes use of CT images that have been scaled to 224×224 pixels with three channels and normalized using ImageNet statistics. A 7x7 convolutional layer with 64 filters and a stride of 2 is used at first. After that, it undergoes 3×3 max pooling with a stride of 2, batch normalization, and ReLU activation. In the center of the network are four residual stages. Two convolutional layers with batch normalization and ReLU are present in each stage. Shortcut connections in these residual blocks allow the input to bypass the convolutions, making it easier for gradients to traverse the network. Feature maps are downsampled using a projection shortcut in the first block of each subsequent step. Following these layers, the spatial dimensions are converted into a 1×1×512 feature vector by an adaptive average pooling layer. This feature vector is then flattened and sent to a fully connected layer that has six neurons representing the various hemorrhage types. Because different types of hemorrhages may occur simultaneously in clinical settings, a sigmoid activation assigns a probability to each class, allowing for multi-label predictions. This method enables the model to rapidly learn small patterns in CT scans, enabling it to detect various types of bleeding precisely and quickly enough for clinical application.

IV. RESULT ANALYSIS

By beginning with ImageNet pretrained weights, the design makes use of transfer learning. Even though the domains are different, this has proven effective for medical image analysis jobs. Given that patients may experience multiple types of hemorrhages simultaneously, making mutually exclusive classification ineffective, the multi-label classification method with sigmoid activation is highly effective in detecting brain hemorrhages. The best balance between model complexity and performance is achieved by the ResNet18 backbone. The vanishing gradient issue that frequently arises in deeper networks is resolved by residual connections, which also maintain the model's efficiency for real-time clinical application.

Five types of brain hemorrhages—epidural, intraparenchymal, intraventricular, subarachnoid, and subdural—were categorized using DenseNet121. This is due to its large number of connections, rapid gradient propagation, and ability to detect both high-level and low-level information from CT scans. Images that have been scaled to 224×224 pixels with three channels and normalized using ImageNet statistics are fed into the network along with pretrained weights. There are four dense blocks with transition layers between the 121 layers that make up the convolutional backbone. In order to facilitate feature reuse and proper gradient flow, each layer receives feature mappings from all layers that came before it. Following the dense blocks, the spatial dimensions are condensed by an adaptive average pooling layer. A fully connected layer with six neurons—one for each type of bleeding—receives the resultant 1×1×1024 feature vector. Since a single CT scan can reveal multiple types of hemorrhage, a sigmoid activation generates distinct probabilities for each class, enabling multi-label classification. To broaden the model, we trained it using a combination of label-smoothed binary cross-entropy and mixup augmentation using the AdamW optimizer and a cosine annealing learning rate schedule. The model with the lowest validation loss was kept for inference, and early stopping was employed to prevent overfitting.

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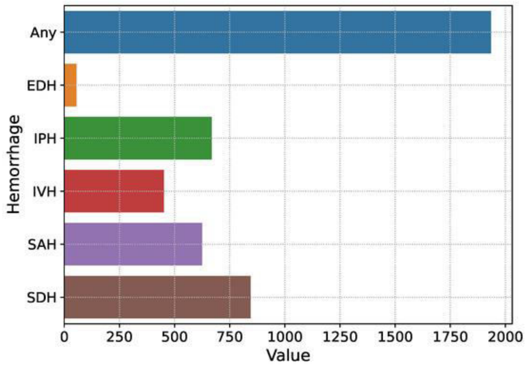

Fig 3: Intracranial Hemorrhage Detection Using Parallel Deep Convolutional Models

A separate set of 50,000 CT scan images was used to test the trained model in order to ensure that the outcomes were equitable. Finding the five types of intracranial hemorrhages—epidural, intraparenchymal, intraventricular, subarachnoid, and subdural—was the primary objective of the assessment. To assess the effectiveness of the categorization, we looked at a variety of performance metrics, such as accuracy, precision, recall, and F1-score. We were able to identify situations where we might be overfitting or underfitting thanks to this. The findings demonstrated that the majority of subtypes could be effectively generalized. However, due to a lack of sufficient examples, performance was somewhat worse for uncommon categories such as epidural hemorrhage. To strengthen the model, any necessary adjustments were made, such as regularizing it and modifying the hyperparameters.

V. CONCLUSION

This study shows how intracranial hemorrhage (ICH) on CT scans can be automatically identified and categorized using deep learning models, specifically ResNet-18 and DenseNet-121. By using convolutional neural networks and advanced preprocessing techniques, the system aims to address the shortcomings of manual radiological interpretation, including time delays, diagnostic errors, and difficulties differentiating between hemorrhage subtypes. Accurately identifying ICH and its subtypes is crucial because treatment plans and patient outcomes depend on a timely and precise diagnosis. When integrated into clinical workflows, AI-powered solutions can significantly reduce radiologists' workloads, expedite emergency decision-making, and improve patient survival and recovery rates. Additionally, the use of interpretability techniques like Grad-CAM enhances clinician trust by making model predictions more transparent. Although further validation on multiple datasets and real-world clinical settings is needed, the results of this study point to a promising future in which AI-driven systems function as reliable decision-support tools in neuroimaging. In the end, this approach has the potential to completely transform emergency care by integrating speed, accuracy, and interpretability in the diagnosis of ICH.

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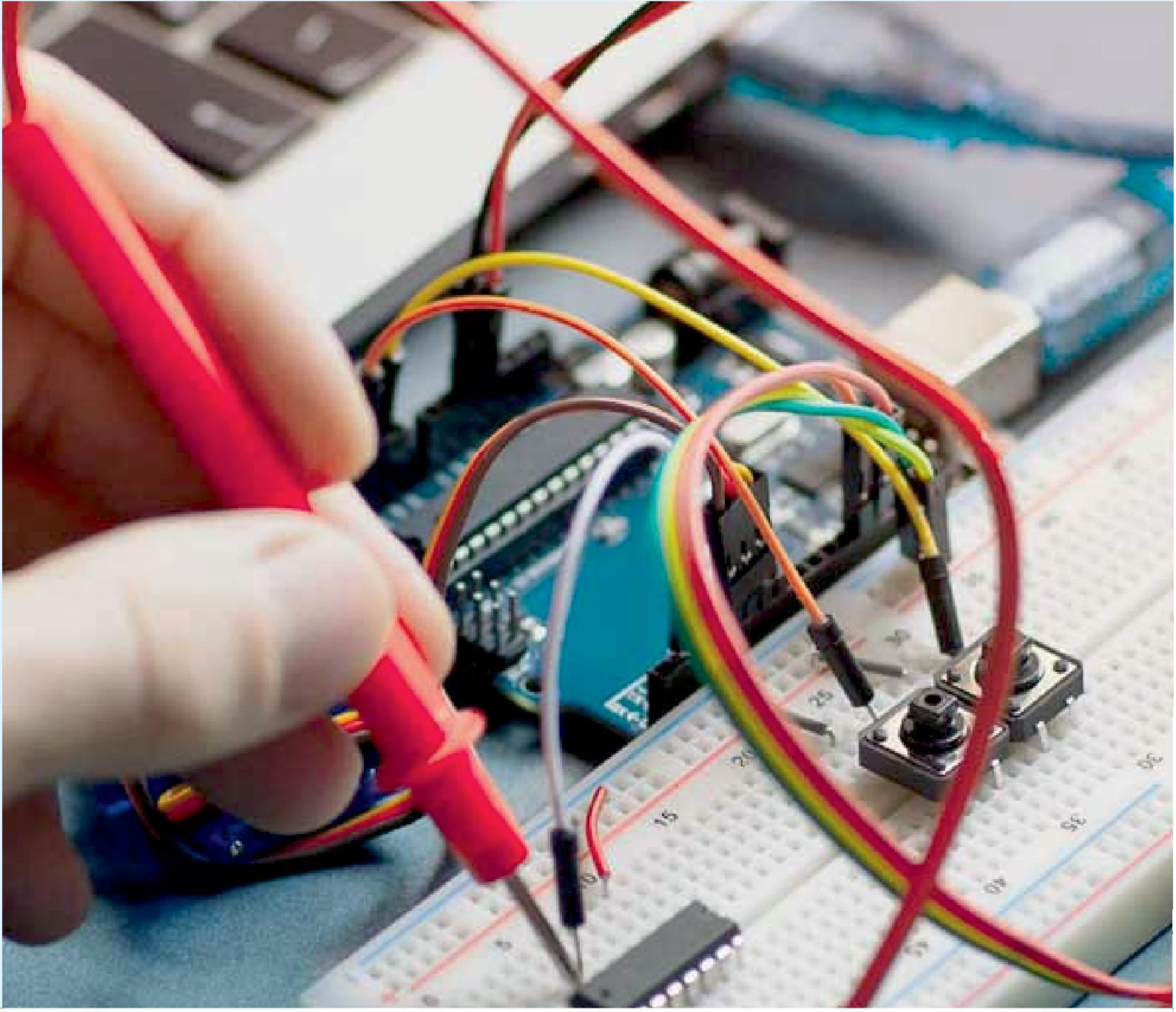

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