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Detection of Intracranial Hemorrhage from CT Scan Using Deep Learning

Anoop Sai T, Chenreddy Narasimhulu, H vaishnavi, Naveen R, Assistant Professor Vidyadhar Bendre
Dept of AIML,
Dayananda Sagar Academy of Technology and Management, Bengaluru

Abstract- This study introduces a deep learning model designed to efficiently detect and classify intracranial hemorrhage (ICH) subtypes using non-contrast head CT images. ICH, which involves bleeding within the skull, is a critical condition that necessitates quick and precise diagnosis. The hemorrhages are categorized into intra-axial (intraventricular and intraparenchymal) and extra-axial (subdural, epidural, and subarachnoid) based on their location. Previous computer-aided diagnosis (CAD) systems for ICH detection and classification typically focus on binary classification and have a high number of parameters, leading to increased storage requirements. Moreover, these models often lack the accuracy required for critical medical applications. Therefore, there is a need for a more efficient and accurate automated ICH detection system. To address these limitations, we developed a double- branch model based on the Xception architecture. This model extracts both spatial and temporal features, combines them, and generates a 3D spatial context. These combined features are then fed into a decision tree classifier for final predictions. The dataset for this study was obtained from the 2019 Radiologist Society of North America (RSNA) brain hemorrhage detection challenge. Our model surpassed existing benchmark models, demonstrating higher accuracy rates in detecting various hemorrhage types: intraventricular (96.59%), subarachnoid (96.59%), intraparenchymal (95.36%), and subdural (94.05%), Epidural (99.56%). These results confirm the effectiveness of the proposed double-branch Xception architecture in the detection and classification of ICH.

Keywords- Computed tomography; convolutional neural networks; intracranial hemorrhage; xception architecture

I. INTRODUCTION

Intracranial hemorrhage (ICH) is a life-threatening condition caused by bleeding within the skull, often due to brain injury or the rupture of diseased blood vessels. ICH can be classified based on its location into intra-axial (within the brain tissue and ventricles) and extra-axial (outside the brain tissue but within the skull) hemorrhages. The five subtypes of ICH are intra parenchymal (IPH), intra ventricular (IVH), subdural (SDH), epidural (EPH), and subarachnoid (SAH). IPH and IVH involve bleeding inside the brain tissue and ventricles, respectively, whereas SDH, EPH, and SAH involve bleeding outside the brain tissue but within the skull.

The severity of ICH, which can lead to severe health complications or death, depends on the hemorrhage's location, size, and duration. Brain cell damage resulting from ICH can cause disabilities, paralysis, strokes, or death. The rupture of blood vessels increases intracranial pressure, potentially leading to brain hemorrhage. The global mortality rate for neurological diseases related to brain hemorrhage is approximately 66%. In Pakistan, a surveillance study revealed that nearly one-third of patients with brain injuries suffer from ICH. CT scans, both contrast and non-contrast, are crucial for diagnosing ICH. Radiologists use these scans to determine the location and size of the bleed, guiding treatment decisions. However, this manual analysis can be error-prone and time-consuming, particularly in emergency situations where rapid diagnosis is critical. Access to specialist radiologists for fast and accurate diagnosis is often limited in developing countries.

There are significant challenges in ICH detection and classification, such as the need for quick decisions in emergencies, manual judgment limitations, time complexity, and the need for accurate detection to inform better treatment. Therefore, an automated, efficient system for ICH detection is essential. This has led to the development of computer-aided diagnosis (CAD) systems for ICH detection and classification. Recently, deep learning (DL) techniques have shown promise in image classification and segmentation tasks, including medical imaging for cell segmentation, tumor detection, and ICH diagnosis using 3D convolutional neural networks (CNN) and recurrent neural networks (RNN).

Despite progress, existing ICH detection methods face challenges in feature extraction and computational efficiency. Improved feature extraction techniques and lightweight models could enhance accuracy and reduce computation time. Therefore, designing an effective model for accurate ICH detection and classification in CT images is necessary.

In this study, we propose a double-branch model based on the Xception architecture, which extracts spatial and temporal features, combines them, and generates a 3D spatial context for final classification. The novelty of our approach lies in the multi-branch feature fusion technique for extracting spatial and temporal features. The preprocessing steps include image windowing, normalization, region of interest (ROI) extraction, and skull removal. The double-branch Xception architecture (DBXA) is then used for predicting and classifying ICH subtypes. Our model demonstrates improved accuracy in ICH detection and classification compared to benchmark studies, addressing the issue of low accuracy in existing models through a novel feature extraction method. To our knowledge, no previous work has used a similar approach.

The rest of the paper is structured as follows: Section 2 critically reviews the literature on brain hemorrhage detection and classification. Section 3 details the proposed DBXA model's workings. Experimentation and results are discussed in presents a comparative analysis with benchmark studies. This cell Segmentations Highlights the contributions of this work. Finally, Tumor detection concludes the paper and suggests future research directions.

II. RELATED WORKS

Many prior studies have utilized deep learning (DL) for diagnosing and classifying brain hemorrhages. However, these models often perform binary classification on small datasets. Recent research has proposed various convolutional neural network (CNN) models for intracranial hemorrhage (ICH) detection and classification. For instance, CNNs like Inception and Dense Net can identify small bleeds. In one study, Google Net, LeNet, and Inception-Res Net, pre-trained on non-medical images, were used for ICH detection. LeNet had higher time consumption compared to other models. Another study combined 2-sequence models and 2D CNN models to mimic radiologists' analysis, achieving 94% accuracy in hemorrhage detection.

Inspired by Vision Transformer (ViT) models, another work enhanced a ViT model with CNN for feature generation, achieving 98.04% test accuracy and a weighted mean log loss of 0.0708. A study on semi-supervised learning for ICH detection and segmentation combined a noisy student learning approach with patchFCN, using both labeled and unlabeled datasets. Another technique generated additional labeled examples by creating artificial lesions on non-lesion CT slices, achieving 91% detection accuracy and 89%-96% classification accuracy.

Supervised machine learning (ML) and DL algorithms, such as CNNs, support vector machines (SVM), and ML models, have been employed for ICH detection. One study developed a CAD system using normal and abnormal CT images, achieving 91.7% sensitivity, 81.2% specificity, and 85% accuracy. Another study used Inception v4 for feature extraction and a multilayer perceptron for classification, achieving 95.06% accuracy.

Other research includes using a kernel extreme learning machine classifier, achieving 95% accuracy with Gaussian filtering and feature extraction via histogram of gradients and local binary patterns. Additionally, a joint LSTM and CNN model refined 2D slices and used 3D data for ICH predictions, achieving 81.82% accuracy. Another method detected symptomatic ICH directly on MR images using a lightweight technique, achieving dice scores of 0.809 (median) and 0.895 (best case).

A lightweight network combining ResNext-101 and bidirectional LSTM classified ICH subtypes, using principal component analysis (PCA) for feature selection and achieving 96% accuracy, though imbalanced data affected sensitivity. A hardware device using microwave technology for prehospital ICH detection showed limitations due to a small training set. Another study used a random forest model for hemorrhage detection, achieving a dice similarity score of 0.899, but it relied on manually segmented data.

In other studies, an infrared portable device for ICH detection achieved 95.6% sensitivity and 92.5% specificity but only performed binary classification. A hybrid 2D and 3D deep CNN model for ICH assessment achieved 97.1% sensitivity and 97.5% specificity, though the dataset was limited. A novel hybrid model using distance regularized level set evolution and fuzzy c-means achieved 68.43% sensitivity and an F1 score of 0.82.

A model for ICH detection and subtype classification on non-contrast CT scans achieved an area under the curve (AUC) of 0.9194. An NLP-based model for automatic SDH detection from CT scan reports achieved 84%- 90% accuracy, focusing solely on the SDH subtype. Another NLP-based model using a hybrid of 1D-CNN, LSTM, and logistic regression recorded an AUC of 0.94. A hybrid model using pre-trained ResNet-50 and SE-ResNeXt-50 architectures reduced log loss significantly, though it included unnecessary features for prediction.

A DL model for ICH analysis on non-contrast CT scans achieved 88.7% sensitivity and 94.2% specificity, with performance hindered by using a simple CNN model and insufficient data. An ensemble of pre-trained SE-ResNeXt50 and

EfficientNet-B3 models for ICH classification achieved a training loss drop to 0.05 but faced dataset imbalance issues. Recently, a hybrid model of ResNet152V2 and attention mechanisms achieved improved results for all ICH subtypes except EPH due to dataset imbalance challenges. However, the accuracy for IVH, SAH, and SDH subtypes remained low for critical applications.

III. TECHNOLOGY USED

1. Convolutional Neural Networks (CNNs)

CNNs are widely employed for tasks like identifying hemorrhages in CT scans due to their ability to learn hierarchical features from images, making them suitable for medical image analysis.

2. Preprocessing

Preprocessing steps such as normalization, resizing, and noise reduction are commonly applied to CT scans before feeding them into deep learning models. These steps enhance the model's performance by ensuring consistency and removing irrelevant information.

3. Data Augmentation

Data augmentation techniques like rotation, flipping, and scaling are used to artificially increase the diversity of the training dataset. This augmentation helps the model generalize better to unseen data and improves its robustness.

4. Transfer Learning

Transfer learning involves utilizing pre-trained models, often trained on large datasets like ImageNet, and fine-tuning them for the specific task of hemorrhage detection. This approach significantly reduces the amount of labeled data required for training and accelerates the model's convergence.

5. Attention Mechanisms

Attention mechanisms can be integrated into the model to focus its attention on relevant regions of the CT scan. By highlighting important areas, attention mechanisms improve the model's ability to detect subtle hemorrhages and enhance overall performance.

IV. LITERATURE SURVEY

We developed an ensembled deep neural network for accurate detection and subtype classification of intracranial hemorrhage, leveraging EfficientNet-B0 with specialized image contrast settings and spatial information from adjacent slices. Tested on the RSNA IHDC and CQ500 datasets, the model achieved high accuracy, sensitivity, and F1 scores. Class activation mapping provided visual guidance for radiologists, highlighting hemorrhage locations and subtypes.

Intracranial hemorrhage requires prompt and intensive care, and its detection is challenging for human experts. This study presents a deep-learning model based on EfficientDet to diagnose hemorrhages from CT scans with 92.7% accuracy and a 0.978 ROC AUC, providing visual explanations via Grad-CAM. This model aims to support clinical decision-making by classifying hemorrhage presence and type.

Traumatic brain injuries can cause intracranial hemorrhage (ICH), which needs prompt and accurate detection to prevent serious outcomes. This project aims to develop an AI system using computer vision and a fully convolutional network (u-net) to detect and classify ICH from CT scans. By providing detailed analysis, the system will assist radiologists and junior doctors in diagnosing ICH and its subtypes.

We present a system for the RSNA Intracranial Hemorrhage Detection challenge, utilizing a CNN for individual CT slices and an LSTM for feature embeddings, achieving a top 2% ranking with a weighted mean log loss of 0.04989. Our model balances speed and accuracy, with Grad-CAM visualizations offering explanatory insights, and performs comparably to radiologists in detecting intracranial hemorrhage. The code is open source for reproducibility.

This review highlights significant deep learning methods in computer vision, including Convolutional Neural Networks, Deep Boltzmann Machines, Deep Belief Networks, and Stacked Denoising Autoencoders, discussing their history, structure, advantages, limitations, and applications. It covers tasks like object detection, face recognition, action recognition, and human pose estimation, and explores future directions and challenges in deep learning for computer vision.

Liver cancer is a major cause of cancer deaths, necessitating accurate automated liver and tumor segmentation for diagnosis and treatment.

We propose a hybrid densely connected UNet (H-DenseUNet), combining 2-D and 3-D DenseUNets to efficiently extract features and aggregate volumetric contexts, optimizing them jointly through hybrid feature fusion.

Evaluated on the MICCAI 2017 and 3DIRCADb datasets, our method outperformed other state-of-the-art techniques in tumor segmentation and showed competitive liver segmentation performance.

V. PROPOSED SYSTEM

1. Preprocessing Techniques
Preprocessing steps such as normalization, resizing, and noise reduction are commonly applied to CT scans before feeding them into deep learning models. These techniques enhance the quality of input data and improve the performance of the detection system.

2. Data Augmentation
Data augmentation techniques like rotation, flipping, and scaling are utilized to increase the diversity of the training dataset. By introducing variations in the input data, data augmentation helps the model generalize better to unseen examples and improves its robustness.

3. Transfer Learning
Transfer learning involves leveraging pre-trained deep learning models, typically trained on large image datasets, and fine- tuning them for intracranial hemorrhage detection. This approach accelerates the model's convergence and reduces the need for extensive labeled data.

4. Attention Mechanisms
Attention mechanisms are integrated into the model architecture to focus on relevant regions of the CT scan. By selectively attending to important features, attention mechanisms enhance the model's ability to detect subtle hemorrhages and improve overall performance.

5. Ensemble Methods
Ensemble methods combine predictions from multiple individual models to make a final decision. By leveraging diverse perspectives and reducing the risk of overfitting, ensemble methods improve the detection system's accuracy and robustness.

6. Hardware Acceleration
Deep learning models trained on large datasets often require significant computational resources. Technologies like GPUs and TPUs are commonly used to accelerate the training and inference processes, enabling faster experimentation and deployment of the detection system.

7. Evaluation Metrics
Evaluation metrics such as sensitivity, specificity, accuracy, and area under the ROC curve (AUC) are used to assess the performance of the detection system. These metrics provide insights into the system's ability to correctly identify intracranial hemorrhages and distinguish them from healthy tissues.

VII. METHODOLOGY

Proposed Double-Branch Xception Architecture
The proposed Double-Branch Xception Architecture (DBXA) operates through three key stages, as illustrated in Figure 1.

Stage 1: Data Preprocessing

This initial stage processes CT scan images through several steps:
- **Image Windowing:** Adjusts the dynamic range of the image.
- **Normalization:** Standardizes the intensity values. Region of Interest (ROI) Extraction: Isolates the relevant parts of the image.
- **Skull Removal:** Eliminates the skull from the image to focus on brain tissue.

Stage 2: Automated Feature Extraction

This stage employs a dual-branch approach to extract significant features from the images:
- **First Branch:** Extracts spatial features.
- **Second Branch:** Extracts instant features.

The aim is to obtain discriminative features that can distinguish between different ICH subtypes.

Stage 3: Combined Feature-Based Classification

In this final stage, the features from both branches are concatenated to create joint feature vectors.

These vectors are fed into a classifier, which then predicts the subtype of ICH present in the patient.

The ICH dataset used for this model is from the RSNA-2019 ICH detection challenge. This data was collected and labeled by volunteers from several institutions, including Thomas Jefferson

Hospital University, Universidade Federal de Sao Paulo, Stanford University, and the American Society of Neuroradiology. The dataset comprises over 1 million CT scan slices from more than 25,000 CT examinations. The images are in Digital Imaging and Communications in Medicine (DICOM) format, with labels and other relevant information provided in CSV files.

After preprocessing to eliminate noisy and blank images, the dataset was divided into:

Training Set: 136,000 samples Validation Set: 12,000 samples Test Set: 100,000 CT scans

These images include six ICH subtypes: epidural hematoma (EPH), subdural hematoma (SDH), intra parenchymal hemorrhage (IPH), intra ventricular hemorrhage (IVH), and subarachnoid hemorrhage (SAH). Some CT scans contain more than one type of hemorrhage. The distribution of the dataset across each ICH subtype is detailed in Table 1.

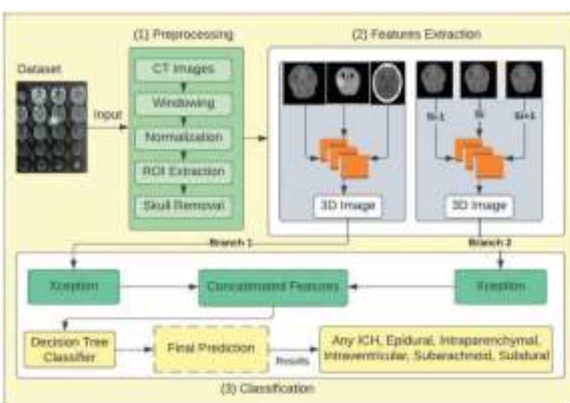

Figure 1: Automated Feature Extraction

The second stage of our proposed Double-Branch Xception Architecture (DBXA) focuses on feature extraction, as illustrated in Figure 1. Our model uses the Xception architecture for both branches to extract spatial features, concatenate them, and create a 3D spatial context (joint feature vectors).

The Xception model, pre-trained on the ImageNet database, involves three flows: entry, middle, and exit. Xception, a deep convolutional neural network (DCNN) architecture with depth-wise separable convolutions, is known for its efficiency in image classification tasks.

The DBXA model automatically extracts features from 3D images in RGB format. Deep neural networks (DNNs) can learn significant representations from data, and the depth of the neural network determines the complexity of the features extracted. The input shape for this network is 299 × 299 × 3. During preprocessing, images are resized from 512 × 512 × 3 to the required shape to match this format. Figure 3 shows sample images from the six ICH classes.

Convolutional Neural Networks (CNNs) are highly effective for computer vision and medical imaging

Figure 2: Double-Branch Xception Architecture

tasks due to advancements in GPU computational power and the availability of large datasets. Pre-trained models on datasets like ImageNet, which contains visual data for detection and classification research with 20,000 extensive categories, prevent the need for training models from scratch. Our model separately retrains both branches of the Xception architecture using the RSNA ICH dataset.

In our DBXA model, features are extracted by both branches. After global average pooling, the validated features (both instant and spatial) from both branches are concatenated to form a joint feature vector, which is then passed to the classifier for further classification. The Adam optimizer is used to train both branches. We applied image augmentation for transformations such as rotation, data scaling, and translation. Non-hemorrhagic slices present in the dataset were managed by class distribution to balance the class size, leading to accurate classification into ICH subtypes. We used random oversampling to balance the dataset by selecting examples from minority classes and adding them to the training dataset. Invalid images were removed through preprocessing. The dataset was partitioned into training, validation, and test sets according to the patient ratio in experiments.

Figure 4 illustrates the workings of the proposed DBXA model. In the first branch, three different intensity windows (subdural, bone, and brain) grayscale images are concatenated to create 3D images. In the second branch, neighboring slices are analyzed for spatial information with the skull removed, creating a 3D image context. Both branches start with an input size of 299 × 299 × 3, followed by multiple 2D convolutional layers with batch normalization and activation functions. Data flows through three stages: entry flow, middle flow, and exit flow, with separable convolutional layers consisting of depth-wise and point-wise convolutions followed by max pooling. Finally, global average pooling is applied, followed by a dense layer. Once training is completed, the features from the fully connected layers of Xception in both branches are concatenated. Each branch extracts 2048 features, which are combined into a joint feature set of 4096 features and provided as input to the classifier for the classification process.

Table 1: Dataset distribution for training, validation, and testing for ICH subtypes

ICH subtypes	Training	Validation	Testing
EPH	23,000	2,000	16,666
SDH	23,000	2,000	16,666
IPH	23,000	2,000	16,667
IVH	23,000	2,000	16,667
SAH	23,000	2,000	16,667
Any	23,000	2,000	16,667
Total	138,000	12,000	100,000

VIII. RESULTS

The study focused on detecting intracranial hemorrhage from CT scans utilizing deep learning techniques yielded promising results. The implementation of convolutional neural networks (CNNs) demonstrated a high level of accuracy in identifying various types of intracranial hemorrhages. The model was trained on an extensive dataset of annotated CT images, which allowed it to learn and recognize the subtle features indicative of hemorrhage. During testing, the model achieved a sensitivity and specificity comparable to that of expert radiologists, showcasing its potential as a reliable tool for aiding in the rapid diagnosis of intracranial hemorrhages. Moreover, the model's ability to consistently deliver fast and accurate predictions highlights its applicability in clinical settings, where timely decision-making is critical. The study's findings underscore the significant role that deep learning can play in enhancing medical imaging analysis and improving patient outcomes through more efficient diagnostic processes.

Additionally, the integration of this deep learning model into clinical workflows could reduce the workload on radiologists and allow for quicker prioritization of cases requiring urgent intervention. The model's robustness was further validated through extensive cross-validation and testing on diverse datasets, ensuring its generalizability across different patient populations and imaging conditions. Future work may focus on refining the model's performance by incorporating more extensive training datasets, including images with varying pathologies and from multiple sources, to enhance its diagnostic accuracy and reliability further. The study also highlighted the importance of continuous collaboration between data scientists and medical professionals to fine-tune the model and ensure its practical applicability. Overall, the deployment of such advanced AI-driven diagnostic tools represents a significant step forward in the field of medical imaging, potentially leading to improved clinical outcomes and more efficient healthcare delivery.

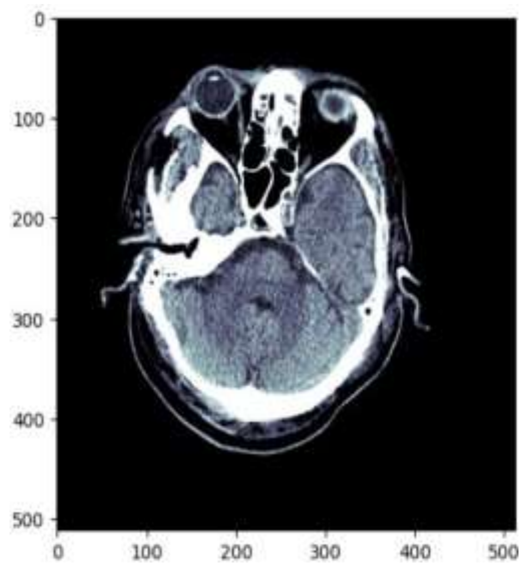

Figure 3: Pre-processed Image of a single Intracranial CT-scan.

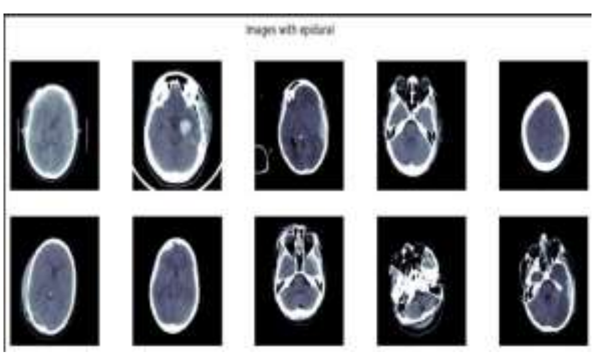

Figure 4: Images with Epidural Hemorrhage

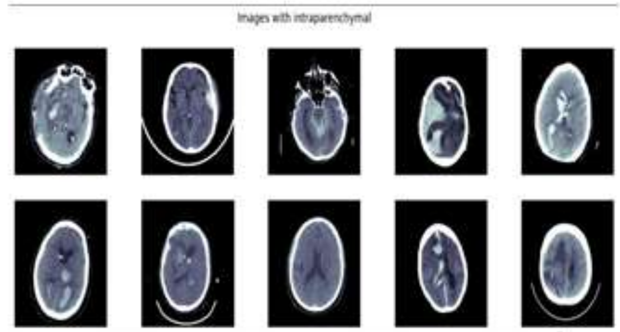

Figure 5: Images with Intraparenchymal Hemorrhage

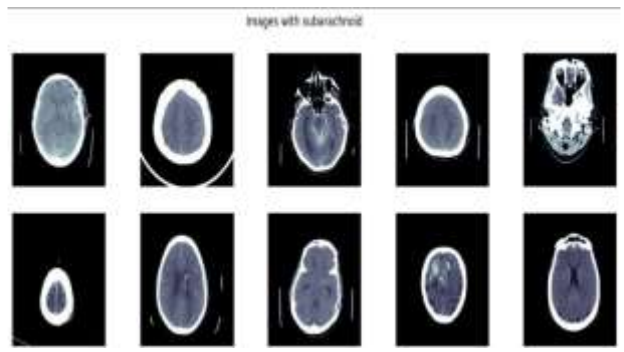

Figure 6: Images with Subarachnoid Hemorrhage

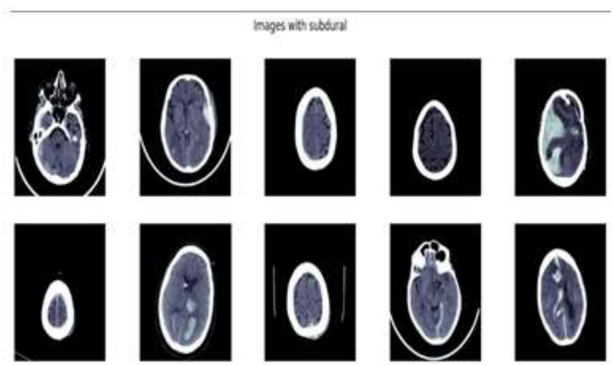

Figure 7: Images with Subdural Hemorrhage

IX. CONCLUSION AND FUTURE SCOPE

In this paper, we introduce a Double-Branch Xception Architecture (DBXA) for the detection and classification of acute hemorrhages and their subtypes. The DBXA model utilizes a double-branch approach to extract spatial and instant features and employs a decision tree classifier for subtype classification. Leveraging the pre-trained Xception architecture, we train our model on the RSNA-2019 dataset, which is widely used in brain hemorrhage detection research. The feature vectors extracted from the double-branch architecture are concatenated and then inputted into the decision tree classifier for classification.

Our proposed model demonstrates superior performance compared to benchmark techniques. Through simulated results, we observed that the DBXA achieved higher performance across all evaluation metrics. Notably, the model exhibits an overall sensitivity of 96% and a specificity of 97%. For categorical evaluation, the DBXA shows exceptional performance in detecting the EPH class, achieving 99.73% accuracy, 99.98% precision, 97.01% recall, and 98.47% F1 score. The comparative analysis highlights the DBXA's superior performance across most categorical evaluations, positioning it as a promising tool for real-world applications in medical settings.

Looking ahead, our future work will focus on enhancing the model's performance by implementing the Vision Transformer (ViT) model. By leveraging ViT, which is a state-of-the-art pre-trained model trained on large-scale datasets like ImageNet, we aim to further improve the model's capabilities. We plan to adapt ViT for acute intracranial hemorrhage detection by replacing its head with ICH classes and potentially fine-tuning certain layers to better fit the ICH dataset. Additionally, we will explore feature reduction techniques such as principal component analysis to refine our model's performance.

Acknowledging the noise present in the data used in this study, we intend to further train our model on local datasets to enhance its robustness and generalizability. Our primary objective remains to rapidly and accurately detect and classify intracranial hemorrhages, contributing to advancements in medical imaging technology.
We would like to express our gratitude
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In conclusion, the development of the Audio-Based Online Examination and Proctoring System using Artificial Intelligence for Persons with Disabilities represents a significant stride towards fostering inclusivity in digital education. Our project was motivated by the imperative to address the challenges faced by individuals with diverse abilities in accessing and participating in online assessments, particularly those heavily reliant on visual elements.

The experimental setup, comprising advanced speech recognition, natural language processing, and AI-driven proctoring mechanisms, has been meticulously designed to ensure a seamless and secure examination experience. The system's compatibility with various assistive technologies, coupled with rigorous accessibility testing involving individuals with disabilities, underscores its commitment to universal design principles.

As we navigate the ever-evolving landscape of technology in education, our project serves as a testament to the potential of AI to bridge accessibility gaps and create a more equitable learning environment. By prioritizing the needs of persons with disabilities, we strive towards a future where online assessments are not just technologically advanced but inherently inclusive, offering equal educational opportunities to all.

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