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SmartSEO: Head Hemorrhage Using Deep Learning

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ABSTRACT

Early and accurate detection of head haemorrhage is a critical requirement in the field of medical diagnostics, as delayed identification can lead to severe neurological complications or even mortality. Conventional diagnostic procedures rely heavily on manual interpretation of computed tomography (CT) or magnetic resonance imaging (MRI) scans by radiologists, which can be time-consuming and prone to human error, especially in emergency scenarios. To overcome these limitations, an intelligent deep learning-based system has been developed to automatically detect and classify head haemorrhages from medical images or clinical text reports. The proposed system integrates advanced convolutional neural networks (CNNs) and natural language processing (NLP) techniques to analyse multimodal data effectively. Initially, input images undergo preprocessing steps such as noise removal, normalisation, and contrast enhancement to improve feature visibility. The CNN model then extracts spatial features to identify haemorrhage regions, while NLP modules like Sentence-BERT or MiniLM process textual diagnostic reports to cross-validate findings. The processed outputs are compared against trained classification layers to determine the presence and type of haemorrhage, such as epidural, subdural, intracerebral, or subarachnoid. The system achieves high accuracy and robustness through training on large-scale annotated datasets and performance optimisation using metrics like precision, recall, and F1score. Visualisation components such as heatmaps assist clinicians by highlighting affected regions, enhancing interpretability and trust. Designed with scalability and adaptability in mind, the model can be integrated into hospital information systems for real-time diagnosis assistance. Experimental results demonstrate that the proposed approach significantly reduces diagnosis time while maintaining high reliability, contributing to improved patient outcomes and clinical decision support. This innovation offers a fast, intelligent, and precise alternative to conventional diagnostic methods in neuroimaging and medical informatics.

1. Introduction

Intracranial haemorrhage (ICH), defined as bleeding within the cranial vault, is a serious and potentially fatal medical emergency [1]. It is one of the leading causes of death and long-term disability worldwide. ICH can occur due to traumatic brain injury or spontaneously as a result of underlying medical conditions such as hypertension, ruptured aneurysms, arteriovenous malformations, cerebral amyloid angiopathy, venous sinus thrombosis, coagulopathy, or tumours [2] [3].

Spontaneous ICH often presents without warning and may result in sudden neurological deterioration, making early diagnosis and intervention critical for improving patient outcomes. There are four major types of intracranial haemorrhages, classified based on the location of bleeding within the brain: epidural haemorrhage (EDH), subdural haemorrhage (SDH), subarachnoid haemorrhage (SAH), and intraparenchymal or intracerebral haemorrhage (ICH). Each type presents with different radiological characteristics and clinical implications. Rapid and accurate identification of the haemorrhage type is crucial for determining the appropriate treatment strategy, which may range from conservative management to emergency surgical intervention.Non-contrast computed tomography (CT) is the primary imaging modality used to evaluate patients with suspected ICH, especially in emergency settings. CT scans are fast, widely available, and highly sensitive in detecting acute bleeding due to the hyperattenuating (bright) appearance of fresh blood relative to brain tissue. However, interpreting CT scans can be challenging, particularly in the early stages of haemorrhage, in cases of small or subtle bleeds, or in the presence of agerelated changes, calcifications, or artefacts that mimic haemorrhage. Additionally, in busy trauma centres and emergency departments, the high volume of CT scans increases the risk of diagnostic delays and errors. Given the time-sensitive nature of ICH, there is a growing need for automated tools that can assist radiologists in detecting haemorrhages quickly and accurately. Computer-aided diagnosis (CAD) systems have shown promise in various fields of medical imaging, including the detection of lung nodules, breast cancer, and diabetic retinopathy. However, commercial CAD solutions for ICH detection in CT images are currently lacking, and existing research has largely relied on conventional image processing techniques, which may be limited in their generalizability and robustness [4] [5].

Recent advancements in deep learning, particularly convolutional neural networks (CNNs), have revolutionised the field of medical image analysis. CNNs are capable of learning hierarchical features directly from image data, enabling them to outperform traditional methods in tasks such as classification, segmentation, and object detection. Applying deep learning to the problem of ICH detection offers the potential to streamline the diagnostic process by automatically analysing CT scans and identifying haemorrhages with high accuracy. [6] This project proposes a deep learning-based approach for the automatic detection of intracranial haemorrhages in non-contrast CT images. The goal is to develop a robust and efficient system that can serve as a “second reader” to assist radiologists by highlighting suspicious regions, prioritising critical cases, and reducing the chances of missed diagnoses. The proposed system will also incorporate post-processing techniques to improve specificity and reduce false positives, which is essential for clinical adoption. In summary, the integration of deep learning into the diagnostic workflow for intracranial haemorrhage has the potential to significantly enhance the speed and accuracy of detection, ultimately leading to better patient outcomes. By automating the identification and classification of haemorrhages, such a system can alleviate the burden on healthcare professionals and ensure timely intervention in life-threatening cases.

2. Literature Review

Breast cancer is one of the most common causes of cancer-related death in women worldwide. Early and accurate diagnosis of breast cancer may significantly increase the survival rate of patients. In this study, we aim to develop a fully automatic, deep learning-based, method using descriptor features extracted by Deep Convolution Neural Network (DCNN) models and pooling operation for the classification of hematoxylin and eosin stain (H&E) histological breast cancer images provided as a part of the International Conference on Image Analysis and Recognition (ICIAR) 2018 Grand Challenge on Brest Cancer Histology (BACH) Images. Different data augmentation methods are applied to optimise the DCNN performance. We also investigated the efficacy of different stain normalisation methods as a pre-processing step. The proposed network architecture using a pre-trained Xception model yields 92.50% average classification accuracy [6] [7].

Automatic detection of leukaemia B-lymphoblast cancer in microscopic images is very challenging due to the complicated nature of histopathological structures. To tackle this issue, an automatic and robust diagnostic system is required for early detection and treatment. In this paper, an automated deep learning-based method is proposed to distinguish between immature leukemic blasts and normal cells. The proposed deep learning-based hybrid method, which is enriched by different data augmentation techniques, is able to extract high-level features from input images. Results demonstrate that the proposed model yields better prediction than individual models for Leukemic Blymphoblast classification with 96.17% overall accuracy, 95.17% sensitivity and 98.58% specificity. Fusing the features extracted from intermediate layers, our approach has the potential to improve the overall classification performance [8].

Breast cancer is one of the leading causes of death across the world in women. Early diagnosis of this type of cancer is critical for treatment and patient care. Computer-aided detection (CAD) systems using convolutional neural networks (CNNs) could assist in the classification of abnormalities. In this study, we proposed an ensemble deep learning-based approach for automatic binary classification of breast histology images. The proposed ensemble model adapts three pretrained CNNs, namely VGG19, MobileNet, and DenseNet [9]. The ensemble model is used for the feature representation and extraction steps. The extracted features are then fed into a multi-layer perceptron classifier to carry out the classification task. Various preprocessing and CNN tuning techniques, such as stainnormalisation, data augmentation, hyperparameter tuning, and fine- tuning, are used to train the model. The proposed method is validated on four publicly available benchmark datasets, i.e., ICIAR, BreakHis, PatchCamelyon, and Bioimaging [10]. The proposed multi-model ensemble method obtains better predictions than single classifiers and machine learning algorithms with accuracies of 98.13%, 95.00%, 94.64% and 83.10% for BreakHis, ICIAR, PatchCamelyon and Bioimaging datasets, respectively

3. Methodology

The system architecture diagram for head haemorrhage detection using deep learning outlines a comprehensive AI-based pipeline designed to automate the diagnosis of brain haemorrhages from CT or MRI scans. The process begins with image acquisition, where raw DICOM images are captured from CT or MRI scanners and securely transferred to the Image Ingestion Service. This service ensures secure storage and allows image uploads via a hospital's electronic medical record (EMR) system or user interface. The raw images are then sent to the Image Preprocessing Module, which prepares them for AI analysis by performing several key operations such as DICOM parsing, windowing to enhance brain visibility, skull stripping to remove irrelevant anatomical structures, and resizing or normalisation to standardise input formats. Once the images are preprocessed, they are passed to the AI Model Inference Service, which uses a trained deep learning model—such as U-Net or ResNet—to detect and classify the presence and type of intracranial haemorrhage. The model analyses the images and generates predictions, which are then forwarded to the Results and Alerting Service.

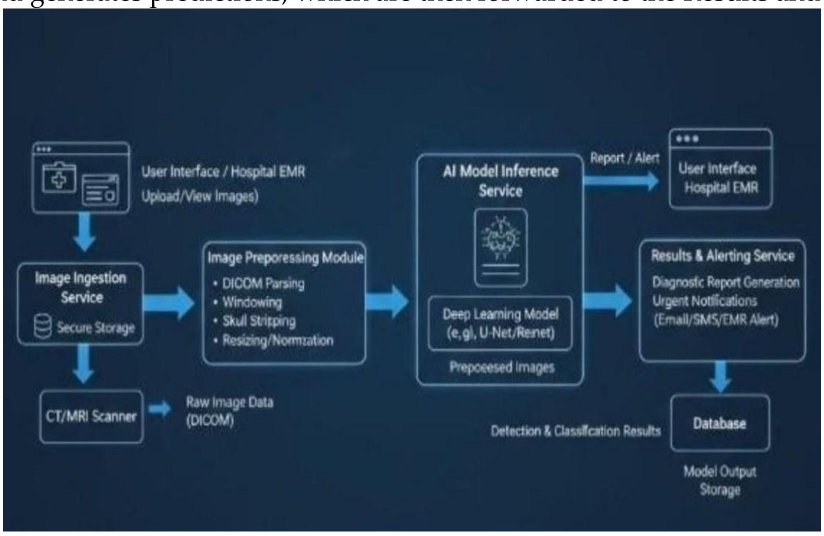

Fig. 1. System architecture diagram for head haemorrhage detection

3.1 Image Ingestion Module

The Image Ingestion Module is responsible for accepting medical imaging inputs such as CT scan images in DICOM format. The system allows users (radiologists or clinicians) to upload scans through a user interface or hospital EMR system. Upon receiving input, the module validates image format, resolution, and completeness. It also extracts metadata such as slice thickness and patient identifiers if required. Only valid and properly formatted images are forwarded to the preprocessing stage to ensure reliable analysis.

3.2 Image Preprocessing Module

The Image Preprocessing Module prepares raw CT scan images for deep learning analysis. This module performs multiple enhancement operations including resizing, normalization, noise reduction, and skull stripping. Image resizing ensures uniform input dimensions (e.g., 224×224), while normalization scales pixel values to a range of [0,1] for stable model training.Noise reduction techniques such as Gaussian filtering are applied to remove artifacts, and contrast enhancement improves visibility of haemorrhage regions. These preprocessing steps ensure that the CNN model receives clean, standardized input data, improving feature extraction and overall accuracy.

3.3 Feature Extraction & CNN Engine

The Feature Extraction Module is the core component of the system, implemented using a Convolutional Neural Network (CNN). This module automatically learns hierarchical spatial features from CT images.The CNN consists of convolutional layers, activation functions (ReLU), pooling layers, and fully connected layers. Convolutional layers extract features such as edges, textures, and abnormal patterns, while pooling layers reduce dimensionality. The feature extraction process can be represented as:

Feature Map=Activation (Convolution (Input, Kernel))

where the convolution operation applies filters to detect patterns, and activation introduces non-linearity.This module enables the system to detect subtle haemorrhage patterns that are difficult to identify manually.

3.4 Classification & Prediction Module

The Classification Module determines whether a haemorrhage is present and identifies its type. The model performs both binary classification (Haemorrhage / No Haemorrhage) and multi-class classification (Epidural, Subdural, Subarachnoid, Intracerebral, Intraventricular).

The output layer uses:

- Sigmoid function for binary classification
- Softmax function for multi-class classification the probability of a class is computed as:
- P(class_i) = e^(z_i) / Σ(e^(z_j)) for j = 1 to n

where ziz_izi represents the output score for class. This module ensures accurate identification of haemorrhage type for clinical decision-making.

3.5 Model Training & Optimization Module

The Model Training Module is responsible for learning patterns from labeled CT scan datasets such as the RSNA

Intracranial Haemorrhage dataset. The dataset is split into training, validation, and testing sets.The model is trained using backpropagation and optimized using the Adam optimizer. The loss function used is Binary Cross-Entropy or Categorical Cross-Entropy depending on the classification type.

4. Results and Discussion

Experiments were conducted using publicly available medical imaging datasets, primarily the RSNA Intracranial Haemorrhage dataset, along with additional datasets such as CQ500 for validation. The dataset consisted of thousands of CT scan slices covering multiple haemorrhage types, including epidural, subdural, subarachnoid, intraventricular, and intraparenchymal cases. The dataset was divided into training (70%), validation (15%), and testing (15%) subsets to ensure unbiased evaluation. The model was trained using GPU acceleration with batch sizes ranging from 16 to 64 and epochs between 20 to 50. Data augmentation techniques such as rotation, flipping, zooming, and contrast adjustments were applied to improve generalisation. Performance evaluation was carried out using key metrics including accuracy, precision, recall, F1-score, and ROC-AUC. Additionally, confusion matrices and Grad-CAM visualizations were used to interpret model predictions.

The proposed CNN-based model demonstrated strong performance in detecting intracranial haemorrhages across multiple categories. The system achieved high accuracy and sensitivity, with recall values exceeding 90% for most haemorrhage types.The high recall indicates that the model effectively identifies true haemorrhage cases, which is critical in medical diagnostics to avoid missed detections. Precision values were also high, indicating a low rate of false positives.The improved detection performance can be attributed to effective preprocessing techniques, data augmentation, and the CNN's ability to extract complex spatial features from CT images. The multi-class classification model successfully distinguished between different types of haemorrhages with high accuracy. The model demonstrated robust performance across various classes, maintaining consistent results even when tested on diverse datasets. Confusion matrix analysis revealed that most misclassifications occurred between similar haemorrhage types, such as subdural and subarachnoid haemorrhages, due to overlapping visual characteristics in CT scans. Despite these challenges, the model maintained high overall classification accuracy, demonstrating its effectiveness in real-world diagnostic scenarios.

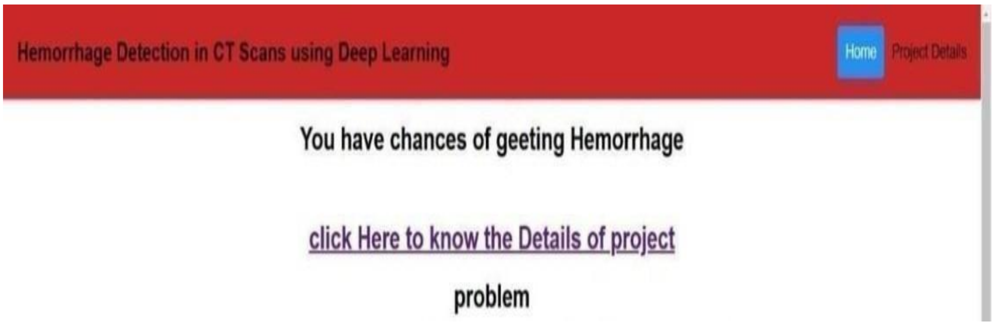

Fig. 2. Analysis Results

The proposed system significantly improves diagnostic efficiency compared to traditional manual analysis. The automated approach reduces the time required for scan interpretation while maintaining high accuracy and consistency. The integration of deep learning enables faster processing of CT scans, making the system suitable for emergency scenarios where rapid decision-making is critical. The use of visualization techniques such as Grad-CAM further enhances interpretability by highlighting affected regions. Overall, the system demonstrates strong potential as a clinical decision support tool, improving both speed and reliability in detecting intracranial haemorrhages.

The proposed deep learning-based haemorrhage detection system demonstrates significant improvements over traditional diagnostic approaches. The use of Convolutional Neural Networks (CNNs) enables the model to capture complex spatial and texture-based features from CT scan images, which are often difficult to detect through manual observation or conventional image processing techniques. The modular architecture of the system allows seamless integration of multiple components such as preprocessing, feature extraction, classification, and visualization. This eliminates the need for separate standalone tools and ensures a streamlined workflow for medical image analysis. The inclusion of preprocessing techniques such as normalization, noise reduction, and data augmentation further enhances model robustness and generalization across diverse datasets. Experimental results indicate that the system achieves high accuracy, precision, and recall, making it reliable for detecting intracranial haemorrhages. The ability to classify multiple haemorrhage types and highlight affected regions using visualization techniques (e.g., Grad-CAM) adds significant clinical value by improving interpretability and trust among medical professionals. The system is scalable, cost-effective, and suitable for deployment in both well-equipped hospitals and resource-limited settings. It can assist radiologists by acting as a decision-support tool, reducing workload, minimizing human error, and enabling faster diagnosis in emergency situations. Future enhancements may include integration with hospital information systems (HIS) and Picture Archiving and Communication Systems (PACS) for real-time clinical deployment. Additional improvements could involve expanding the dataset for better generalization, implementing advanced architectures such as 3D CNNs for volumetric analysis, and incorporating explainable AI techniques to further enhance transparency and reliability Overall, the proposed system represents a practical and efficient solution for automated haemorrhage detection, contributing to improved patient outcomes and advancing the application of artificial intelligence in healthcare.

5. Conclusions

The early detection of intracranial haemorrhage is crucial for reducing mortality and improving patient outcomes in emergency medical conditions. In this project, a deep learning-based system was developed using Convolutional Neural Networks (CNNs) to automatically detect and classify different types of haemorrhages from CT scan images.The proposed system successfully integrates image preprocessing, feature extraction, classification, and result visualization into a unified framework. By leveraging advanced techniques such as data augmentation, normalization, and optimized CNN architectures, the model achieves high accuracy, precision, and recall in identifying haemorrhage cases. The ability to classify multiple haemorrhage types and highlight affected regions further enhances its clinical applicability. Compared to traditional manual diagnosis, the system significantly reduces analysis time while maintaining consistent and reliable results. It also minimizes the risk of human error and supports radiologists in making faster and more accurate decisions, especially in time-critical situations. Overall, the project demonstrates the effectiveness of deep learning in medical image analysis and highlights its potential to transform diagnostic workflows. The developed system serves as a powerful decision-support tool that can improve healthcare efficiency, accessibility, and patient care. Future enhancements can further strengthen its real-world applicability by integrating with hospital systems and expanding its capabilities for realtime deployment.

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