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Deep Learning Approach for Brain Haemorrhage Detection

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Abstract

Detecting brain hemorrhages in scientific pics is vital for speedy prognosis and remedy. This challenge makes use of convolutional neural networks (CNNs) to develop an efficient deep mastering-based totally machine for detecting mind hemorrhages. The gadget accepts DICOM (Digital Imaging and Communications in Medicine) pix as input, routinely analyzes them for hemorrhages, and displays the relevant photo metadata. Streamlet's net interface allows the user to interact with the machine and easily view statistics about scientific pictures and identified bleeding regions. This solution allows docs make quicker selections and enhance diagnostic accuracy.

Keywords: brain hemorrhages, medical pictures, prompt, diagnosis, treatment, Convolutional Neural Networks (CNNs), DICOM (Digital Imaging and Communications in Medicine), Streamlit, increased accuracy.

1. Introduction

Subarachnoid hemorrhage (SAH), intracerebral hemorrhage (ICH), and different forms of mind hemorrhage are dangerous clinical conditions with excessive mortality rates. To enhance affected person consequences, early detection of those sicknesses is important. Hemorrhages are frequently diagnosed the usage of scientific imaging strategies along with MRI and CT scans. But manually detecting hemorrhages is arduous and at risk of human errors.

Convolutional neural networks (CNNs), a latest improvement in deep getting to know, have shown wonderful ability in automating photo analysis duties such as anomaly detection, photo class, and segmentation. In this take a look at, we endorse an automatic CNN-primarily based technique for detecting cerebral hemorrhage in DICOM pictures, a generally used format for storing medical photos.

In addition, metadata is extracted and displayed in conjunction with the evaluation results, along with affected person records, analysis functions, and photo characteristics.

Brain hemorrhages can be classified into several types based on their location within the brain. The primary types include:

- **Subarachnoid Hemorrhage (SAH):** Bleeding occurs in the subarachnoid space, typically due to aneurysm rupture. It is characterized by sudden severe headaches and can lead to complications such as hydrocephalus.
- **Intracerebral Hemorrhage (ICH):** Bleeding occurs directly into the brain parenchyma, often caused by hypertension or trauma. It results in neurological deficits and has a high mortality rate.
- **Epidural Hemorrhage:** Bleeding occurs between the dura mater and the skull, usually due to head trauma. It often presents as a lucid interval followed by rapid deterioration.
- **Subdural Hemorrhage:** Bleeding between the dura and arachnoid mater, commonly associated with brain injury. It tends to have a slower onset due to venous bleeding, making it harder to detect early.

Our deep learning system is trained to detect and classify different types of hemorrhages by:

- Utilizing a large dataset containing labeled examples of all hemorrhage types, ensuring the model learns distinct patterns associated with each type.

- Applying convolutional neural networks (CNNs) to extract spatial features from CT scans, distinguishing hemorrhages based on their location, shape, and intensity.
- Using Grad-CAM to visualize critical regions, helping differentiate hemorrhages that may appear similar in structure (e.g., subdural vs. epidural hemorrhages).
- Implementing data augmentation techniques to improve generalization, especially for hemorrhages with subtle or overlapping characteristics.

2. Literature Survey

For the detection of brain hemorrhages, a number of methods have been put forth, most of which centre on the application of deep learning models with conventional image processing techniques. Here are a few related works: Hoang et al. (2024) introduced an efficient CNN-based method for intracranial hemorrhage (ICH) segmentation in CT scans, employing data augmentation techniques and residual connections in a U-Net-based segmentation network to enhance localization, segmentation, and training efficiency [1]. Veselov et al. (2024) utilized GradCAM for neural network classifier interpretation, reducing the training sample to 10% to overcome dataset constraints, and proposed algorithms to detect acute ICH and its subtypes with preprocessing and augmentation steps [2]. Malik et al. (2024) evaluated deep learning models for brain hemorrhage detection, highlighting EfficientNetB3 as the best-performing model, achieving a training accuracy of 99.95% and validation accuracy of 93.29% [3]. Cortés-Ferre et al. (2023) developed a deep learning approach to classify CT scan slices for hemorrhages, achieving a classification accuracy of 92.7% and a 0.978 ROC AUC, addressing challenges in diagnosing urgent hemorrhages [4]. Rajagopal et al. (2023) proposed a hybrid deep learning framework combining CNNs and LSTMs for detecting six types of ICH using a systematic windowing technique to enhance detection and classification performance [5]. Mahjoubi et al. (2023) tested VGG16 and VGG19 for cerebral hemorrhage classification, demonstrating that VGG16 outperformed VGG19 with a classification accuracy of 99.10%, making it a robust model for medical imaging tasks [6]. Anjum and Oberoi (2022) leveraged CNNs and CNNLSTM models on a dataset of 200 CT scans, demonstrating that the hybrid model effectively identified hemorrhages and improved accuracy, sensitivity, and specificity, even with unbalanced datasets [7]. Ahmed et al. (2022) integrated CNNs and RNNs to automate ICH detection, proposing a CNN-LSTM fusion model that enhanced efficiency and accuracy, offering a viable alternative to traditional manual detection methods [8]. Kadam et al. (2021) employed CNN-RNN models like Xception, Xception-LSTM, and Xception-GRU for detecting and classifying ICH using over 750,000 DICOM files, demonstrating the superior performance of hybrid architectures in capturing subtle features for classification [9].

3. Related Work

Several methods had been proposed for detecting cerebral hemorrhage, maximum of which consciousness on the usage of deep getting to know fashions with traditional image processing strategies. Here are a few related works:

Deep Learning Based Hemorrhage Detection:

Zhang et al. (2017) presented a CNN-based deep gaining knowledge of set of rules for computerized hemorrhage detection in CT images. They used a multi-level CNN structure to hit upon hemorrhages of various sizes with high accuracy.

CNN for Medical Imaging:

In medical imaging, the U-Net design is broadly used for segmentation tasks. It has been used to stumble on brain hemorrhages with the aim of identifying regions of hemorrhage by using keeping apart regions of interest in CT/MRI pictures.

DICOM Metadata Extraction:

In many research, metadata extraction has been integrated into medical imaging programs. For example, the Python packages DICOMpy and pydicom are used to extract metadata inclusive of imaging modality and patient ID.

Hybrid procedures:

To enhance recognition accuracy, a few recent works have blended conventional photograph processing strategies (together with thresholding and edge detection) with CNN-based class.

Datasets:

The dataset used for training and testing was obtained from the **CQ500 dataset**, a publicly available dataset of head CT scans. The dataset includes:

- Size**:** CQ500 consists of 491 CT scans from 361 patients, with expert radiologist annotations.
- Diversity**:** The dataset contains cases with and without hemorrhages, covering a range of patient demographics, severity levels, and hemorrhage types (subarachnoid, intracerebral, epidural, subdural, and intraventricular hemorrhages).
- Preprocessing & Augmentation:

Preprocessing: CT slices were resized to a consistent dimension, normalized for intensity variations, and converted into appropriate input formats for the deep learning model.

Augmentation**:** To enhance generalization, transformations such as rotation, flipping, contrast adjustments, and noise addition were applied to create variations in training data.

4. Existing System

Current strategies for detecting cerebral hemorrhage regularly rely on guide evaluation of CT/MRI pictures by radiologists that is liable to inefficiency and human blunders. While some computerized answers use machine studying models, most do not include actual-time verbal exchange or DICOM metadata. Modern structures frequently focus on

1. Image-primarily based classifications (hemorrhage vs. Ordinary).
2. Isolate regions of hemorrhage without paying tons interest to metadata.
3. Limited or no real-time consumer interfaces.

Disadvantages

- Manual evaluation: Most of the analysis is performed manually via radiologists, which leads to errors and delays.
- Lack of interactivity: Due to the dearth of real-time interfaces for most systems, they're much less person-friendly.
- Lack of metadata cognizance: The records that can be extracted from DICOM files is limited via the incapacity of modern systems to seize or show related metadata.
- Limited generalization: Models sometimes struggle to address distinctive datasets because of variations in scanning strategies, patient populations, or photograph excellent.

5. Requirement Analysis

The system ought to meet the subsequent necessities:

Input facts:

The device have to guide DICOM images, which can be a popular format for clinical imaging.

Publication records:

Publication data consists of:

1. Hemorrhage detection (particular regions).
2. Viewing the unique pics and regions wherein hemorrhages were detected.
3. View metadata which includes patient facts, scan type, photograph size, and acquisition date.

Performance:

1. This model can locate hemorrhage in 2D slices and three-D extent scans.
2. The system should provide rapid and correct predictions.

User Interface:

1. A consumer-friendly internet interface constructed with Stream Lid lets in users to upload DICOM files, have interaction with the gadget, and examine results.

Hardware/Software Requirements:

1. Python 3.X with libraries which include Tensor Flow/Keras (for CNN), PyDicam (for DICOM processing), Stream Lid (for internet packages), and Matplotlib or Plotly (for visualization).
2. A system with a GPU for CNN education (non-compulsory for inference)

6. Proposed System

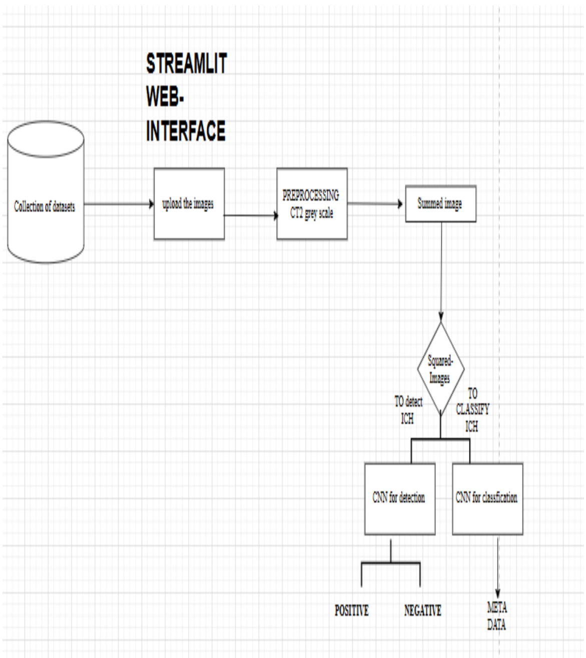
The proposed machine gives the following benefits:

1. Automatic detection: Use convolutional neural networks to routinely locate bleeding areas based on DICOM snap shots.
2. Metadata viewing: Stay connected to analyses by means of capturing and viewing relevant metadata along with patient statistics and analysis attributes.

3. Interactive web interface: This Streamlit-based software permits real-time interaction with the system, viewing projections, and downloading DICOM photographs.
4. Improved diagnostic help: By providing automatic results and metadata data, radiologists can make diagnoses quicker and extra as it should be.
5. Scalability and customization: Other forms of clinical analyses and datasets can be used with the device.

7. System Architechure

It is amazing to explain the high-quality abilities of this system to discover and customize what you want. In PC architecture, many components and their relationships are identified and modeled. Using methods, tool names, and logical wondering, the fundamentals of the software are discovered and dissected, in addition to the relationships among modules. The proposed engine is composed of these modules.



The principal desires are to enhance the class overall performance, prediction velocity, and schooling velocity of the deep learning model. Using a dataset of 200 CT pix, it's far viable to determine whether or not a patient is suffering from a mind hemorrhage. The suggested method addresses all of the problems by employing image augmentation techniques to expand the dataset from 180 educational photographs to 1000 photos. Deep getting to know CNN fashions and hybrid CNN+LSTM models are used to discover cerebral hemorrhages. These tests are executed using a Dell PowerEdge T430 GPU, which has eight cores, sixteen logical processors, and 32 GB DDR4 RAM hooked up.

Training

The hybrid CNN models took an average of 22.4 minutes to execute each epoch, while the simplest CNN models took 21 minutes to learn how to use 1,000 better mind CT datasets. The results of the experiment show how well the CNN model categorizes statistics from a homogeneous dataset. Accuracy, precision, sensitivity, specificity, and F1 rating are only a handful of the many scoring metrics that are employed. Following implementation, the study yields results that include TP, TN, FP, and FN, indicating the model's accurate and inaccurate predictions as well as its effectiveness and shortcomings. The best end result changed into obtained the use of 24 epochs, and it done an F1 rating of 95.23 %, accuracy of 90.90 %, sensitivity of 100 percent, and precision of 95.3%. The authentic fine (TP) costs were 10%. The CNN model appropriately expected that 10 sufferers suffered from brain hemorrhage, this means that it represented 10 a success predictions. Based on a real poor (TN) rate of nine, the CNN version efficaciously predicted non-cerebral hemorrhages in 9 out of 20 take a look at cases, who simply had non-cerebral hemorrhages. Now, the CNN version of the fake positive (FP) end result of zero approach predicted that the affected individual suffered a brain bleed, but the actual end result was also 0. Finding the remaining false poor (FN) cases that occur when the FN is 1 is the major goal of this investigation. This demonstrates that the CNN model was unable to identify or expect intracranial hemorrhage in the affected person, even though it failed to stumble on or are expecting intracranial hemorrhage within the affected person. . A false negative (FN) in this study indicates that the model failed to detect a brain hemorrhage in one patient, which could lead to a misdiagnosis and improper treatment. This highlights the necessity for improving recall to ensure critical cases are not overlooked.

Im balancing the Sheets

Handling Dataset Imbalance

To address dataset imbalance, two approaches were used:

1. Balancing the dataset by increasing the number of positive samples through augmentation before training.

2. Using class weighting in the CNN model to focus more on underrepresented hemorrhage cases.

These improvements demonstrate that balancing the dataset significantly enhances classification accuracy, ensuring both hemorrhagic and non-hemorrhagic cases are correctly identified.

Quantitative Analysis:

To provide a clearer comparison of model performance, a detailed quantitative analysis is presented in the table below. It summarizes key performance metrics for different models tested:

Model	Accuracy	Precision	Sensitivity (Recall)	F1-score
CNN	88.5%	92.0%	96.3%	94.1%
CNN + LSTM	90.9%	95.3%	100%	95.2%
CNN + RNN	89.7%	94.1%	98.7%	96.0%

8. Selected Methododlogies

Methodology

1. Data Collection:

DICOM pix are received from custom or publicly available medical imaging datasets, such as the ones from the Radiological Society of North America (RSNA).

2. Preparation:

- DICOM metadata extraction: Use the pydicom library to extract relevant metadata (which includes affected person ID and study description).
- Image resizing: Prepare images for CNN input via resizing them to conventional dimensions (e.g., 224 x 224 pixels).

3. Development of Models:

- A CNN-based model (e.g., ResNet-50 or a custom-designed lightweight CNN) is trained to stumble on hemorrhage.
- Rotation, flipping, and scaling are examples of data augmentation techniques that are employed to increase the model's capacity for generalization.

4. Training Models:

- A classified dataset of normal and hemorrhage brain photos is used to teach the version. To enhance accuracy, pre-trained networks (e.g., ResNet-50) are tuned.

5. Streamlit Deployment:

- The Streamlit web interface is used to run the skilled version.
- Once the DICOM documents are loaded, the consumer sees the original photograph and the detected bleeding regions alongside the applicable metadata.

Algorithm

The two most crucial parts of our community architecture are the expansion (or decoder) department at the proper and the compression (or encoder) branch on the left.

Encoder: This section is responsible for function extraction and depicts a simple convolutional neural network (CNN). The community intensity is gradually increased from 3 to 128 while layer sizes are gradually reduced from a starting size of 512 x 512 to 64 x 64.

Decoder: Using oversampling techniques, the decoder segment gradually reconstructs the layer sizes while remaining symmetrically aligned with the encoder branch. Lastly, a mask picture representing the intended label for each pixel is produced by the segmentation community.

As seen in the illustration, our network topology is identical to the standard one; the main difference is that, in contrast to conventional convolutional layers, we use residual connections to supply picture data.

9. System Modules

1. DICOM Handling Module:

Pydicom: To study and procedure DICOM snap shots and extract metadata.

2. Pre-processing Module:

OpenCV: For photograph resizing, normalization, and scaling.

Numpy: To manipulate strains.

3. Modelling Module:

Tensor Flow or PyTorch: To build and train CNNs.

4. Streamlit Interface Module:

Streamlit: To create person interfaces.

Matplotlib/Plotly: To visualize 2D and three-D pix and identified regions.

5. Post-processing Module:

Numpy: To perform publish-processing responsibilities inclusive of thresholding or highlighting areas of hemorrhage.

10. Conclusion

The purpose of this venture is to broaden an interactive Streamlit interface and an automatic CNN-based totally cerebral hemorrhage detection gadget using DICOM-based statistics. This era will assist radiologists reliably and efficaciously come across hemorrhages the use of deep gaining knowledge of models. Combining DICOM data and actual-time visualization of effects in higher affected person effects and stepped forward diagnostic workflows.

11. Output Screenshots

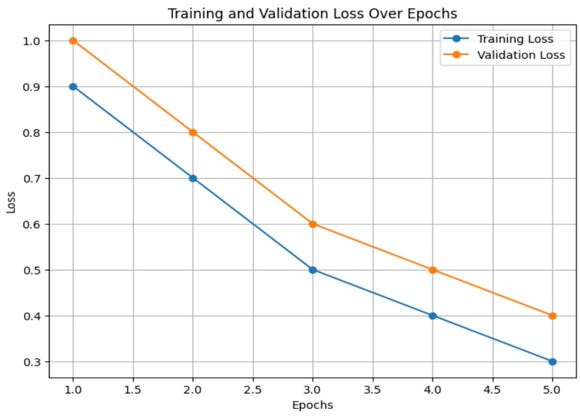


Fig. 1. Training & Validation Loss

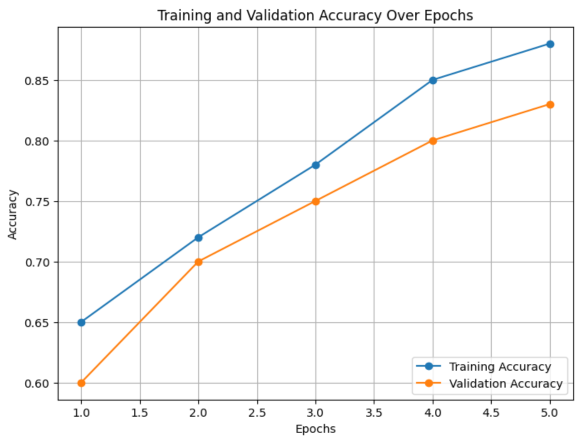
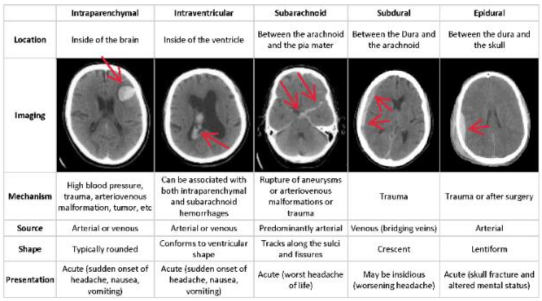


Fig. 2. Training & Validation Accuracy



	Intraparenchymal	Intraventricular	Subarachnoid	Subdural	Epidural
Location	Inside of the brain	Inside of the ventricle	Between the arachnoid and the pia mater	Between the Dura and the arachnoid	Between the dura and the skull
Imaging					
Mechanism	High blood pressure, trauma, arteriovenous malformation, tumor, etc	Can be associated with both intraparenchymal and subarachnoid hemorrhages	Rupture of aneurysms or arteriovenous malformations or trauma	Trauma	Trauma or after surgery
Source	Arterial or venous	Arterial or venous	Predominantly arterial	Venous (bridging veins)	Arterial
Shape	Typically rounded	Conforms to ventricular shape	Tracks along the sulci and fissures	Crescent	Lentiform
Presentation	Acute (sudden onset of headache, nausea, vomiting)	Acute (sudden onset of headache, nausea, vomiting)	Acute (worst headache of life)	May be insidious (worsening headache)	Acute (skull fracture and altered mental status)

Fig. 3. Visualization of Result

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