DEEP LEARNING BASED BRAIN HAEMORRHAGE DETECTION USING CT IMAGES

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ABSTRACT. Intracranial hemorrhage (ICH) is a serious and life-threatening medical condition that requires rapid diagnosis and treatment. This study explores the use of deep learning, specifically the YOLOv8 model, for ICH detection and classification in non-contrast head CT scans. The Brain Hemorrhage Extended (BHX) dataset was used to train and evaluate the model. The YOLOv8 model demonstrated excellent performance, achieving high accuracy and localization in detecting and classifying ICH, even in scenarios with multiple labels per image. Key parameters and model architecture are discussed, as well as potential future works, including the use of larger and more diverse datasets, and the development of explainable AI models. This study contributes to the advancement of AI for medical imaging and timely clinical interventions for ICH.

Keywords: YOLO, Intracranial hemorrhage, CT, Deep learning, Localization

1. Problem Outline

The project "Brain Haemorrhage Detection" focuses on the critical issue of detecting and localising brain haemorrhages, which is a medical emergency condition associated with a high mortality rate. This condition is typically diagnosed through neuroimaging. The early and accurate detection of haemorrhages is a key for ensuring effective treatment. However, the manual inspection of CT scans is a time-consuming process and it highlights the need for automated tools to aid radiologists in this process.

To address this problem, our proposed solution involves developing a deep learning model for the detection and localization of brain haemorrhages in CT images. In this research paper, the primary focus is on improving the accuracy of localizations and efficiency of the model of classifying head computed tomography (CT) scans. The researchers tackle the challenge of identifying small, subtle abnormalities in these scans, which can be life-threatening but are often difficult to detect due to the limitations of CT imaging.

Intracranial Hemorrhages (ICH) have a substantial impact on patient health, with a mortality rate of 40% within one month of onset and those are a major contributor to the occurrence of strokes. ICH can occur in different sections in the brain, therefore localising the detected haemorrhage makes it important for physicians to continue with their treatments. Additionally this information will often be needed for the decisions made such as,the potential risk of cerebral damage, and also for the immediate medical involvements.

The proposed solution aligns with YOLOv8, the latest version of YOLO (You Only Look Once) developed by Ultralytics. As a state-of-the-art (SOTA) model, YOLOv8 introduces new features and improvements in order to enhance performance, flexibility, and efficiency. YOLOv8 is renowned for its real-time object detection capabilities, making it an ideal choice for efficient and accurate image processing. It supports a full range of vision AI tasks, including detection, segmentation, pose estimation, tracking, and classification, which enables the identification of six distinct types of haemorrhages effortlessly. This versatility allows users to leverage YOLOv8's capabilities across diverse applications and domains, ultimately improving patient care and outcomes. By employing YOLOv8, this research aims to enhance the automation of haemorrhage detection, making it a valuable tool for radiologists and healthcare professionals in the field.
Here's a breakdown of the key components of the solution:

1.1. **Data Collection:** The collection of CT images were obtained from a publicly available dataset known as CQ500, maintained by qure.ai. This dataset consists of images with varying characteristics such as thick-slice, thin-slice, bone-filtered, contrast-enhanced, and soft-tissue non-contrast-enhanced series. The dataset also contains bounding box annotations that specify the regions where different types of acute haemorrhages are present. The CQ500 dataset consists of 491 head CT scans that were collected from radiology centres in New Delhi. Among these scans, 205 of them were classified as having positive findings related to haemorrhage.

1.2. **Image Labelling:** To enable the classification of various types of acute haemorrhages, they are labelled and annotated in the head CT images within their dataset. These annotations involve when classifying the images into six distinct categories. Which are;

(1) Intraparenchymal
(2) Subarachnoid
(3) Intraventricular
(4) Epidural
(5) Subdural
(6) Chronic Subdural Hematoma

To perform the image annotations, a combination of three neuroradiologists with varying levels of clinical experience was involved. Their role was to read and annotate the images from the "thick-slice series."
The dataset includes two types of image series:

- "Thick-slices", containing images with a thickness of 3 mm or more.
- "Thin-slices", containing images with a thickness of 1 mm or less.

The "thick-slice" image series were matched with their corresponding "thin-slice" series using the "Image Position (patient)" DICOM tag, a metadata element in medical imaging data that helps to align images correctly.

1.3. **Datasets:** There are 3 versions of datasets to address different research needs.

1_Initial_Manual_Labeling.csv : This version contains only the hand-drawn annotations of the thick-slice images. .

2_Extrapolation_to_All_Series.csv : In this version, there were hand-drawn annotations of the thick-slice images, just like in Version 1. However, it also includes annotations that have been extrapolated to cover all other corresponding images in the dataset. This version is more comprehensive and includes annotations for various image types, including those with bone filters or contrast-enhanced series.

3_Extrapolation_to_Selected_Series.csv : Similar to Version 1, this version includes hand-drawn annotations of the thick-slice images. However, the annotations in this version have been extrapolated only for the selected soft-tissue non-contrast-enhanced series. It is more specialised and focuses on a specific subset of the images.

Therefore, according to this researchers can choose the version that best suits their research needs, depending on the level of detail and specific characteristics they require for their intracranial haemorrhage detection and localization tasks.

2. Existing alternatives

In the field of searching CNN aid solutions in image classification and detection, there has been interesting research focusing on different datasets, different algorithms and so on. Here are some of them.

"Deep Learning algorithms for detection of critical findings in head CT scans"[1]
The research paper focuses on developing a deep learning algorithm for detection of critical findings in non-contrast head CT scans not only its various types but also calvarial fractures, midline shift, and mass effect. The study collected a dataset of 313,318 head CT scans with associated clinical reports. The dataset was divided into two parts: the Qure25k dataset for algorithm validation and a CQ500 dataset for additional validation.

"Imaging of Intracranial Hemorrhage"[2]
The review emphasises the most prevalent vascular causes of ICH while acknowledging that the paper does not aim to cover all possible causes. The key focus lies on ICH resulting from trauma and vascular issues, excluding discussions on ICH associated with primary or metastatic neoplasms. The paper highlights the significance of computed tomography (CT) as the primary imaging modality, particularly in emergency cases, but also discusses the role of Magnetic Resonance Imaging (MRI) in ICH evaluation.

"Expert-Level Detection of Acute Intracranial Hemorrhage on Head Computed Tomography using Deep Learning"[3]
This research paper proposes a new approach using a patch-based fully convolutional

network (PatchFCN) to perform semantic segmentation. In other words, their system aims to not only identify abnormalities but also precisely localize their boundaries within the CT images. The research paper introduces a deep learning model (PatchFCN) that excels in accurately identifying and precisely localizing abnormalities in head CT scans. It also demonstrates innovative strategies for improving data efficiency and scaling in the medical imaging domain.

3. Proposed Method

In our methodology, we aimed to build a solution that goes beyond the conventional methods by focusing on head CT scans rather than MRI images. The decision to exclude MRI images from our approach was deliberate, as CT scans are often more readily accessible in emergency situations, enabling faster diagnosis and intervention.

When selecting our dataset, we made a conscious choice not to use the RSNA dataset because of not having localization and consisting a large amount of data, making it less suitable for our specific research goals. Instead, we chose the qure.ai head CT localized images dataset, which offers distinct advantages.

In the data preprocessing stage, we went for the third category which contains manually labeled annotations along with a collection of selected extrapolated thin slices, providing valuable data resources for our research.We conducted the preprocessing part locally on our computer, ensuring efficient handling of the dataset.

3.1. **Preprocessing.**

3.1.1. *Image-UID Mapping.* Since all the images are in .dcm format, those were collected into a directory containing DICOM (Digital Imaging and Communications in Medicine) images from the CQ500 dataset. Each image contains a unique identity named as SOPUID which is useful when mapping labels stored in the csv files with the image. For that, we maintain a dictionary and if a match is found, the DICOM file path and the annotation data are associated with the same UID and stored together.

3.1.2. *Image Preprocessing.* During the image preprocessing phase, we implement windowing techniques on the CT scan images. This process includes optimising intensity values and adjusting the dataset's contrast and brightness levels. Typically, a DICOM image contains between 12 - 16 bits per pixel. Therefore it should be normalised to the range [0, 255] in order to enhance the visual quality of the images. To remove noise from the images, we use a dilation operation which helps in smoothing and reducing small artefacts or noise in the images. The kernel size can be adjusted as needed and we used a 3x3 kernel for 1 iteration. After all these processes, the image is then converted into a 2D array.

3.1.3. *Saving Processed Images.* To ensure random distribution between the training and validation sets, pre-processed image data are shuffled and splitted into two sections such that 90% of the images go to the training set and the remaining 10% to the validation set and those were saved in respective folders. Those separated images in respective "train image" or "val image" directory were again saved in their corresponding JPG file. We perform that because the yolo only accepts jpg or png. Since we found that jpg is much easier to process, we chose to convert it into jpg. Within this separation process it is coded to create a label file as a text file (.txt) in the corresponding directory.

FIGURE 1. Comparison of the image before and after preprocessing

3.1.4. *Training Model.* For training the model we have used pre-trained weights of the yolov8x model, which were trained using Openimagev7 data-set. Due to the time and resource constraint we could only re-train the model for our dataset only upto 50 epochs, although the results were amazing. Brief analytical reports of the model training is attached below.

4. Results and Discussion

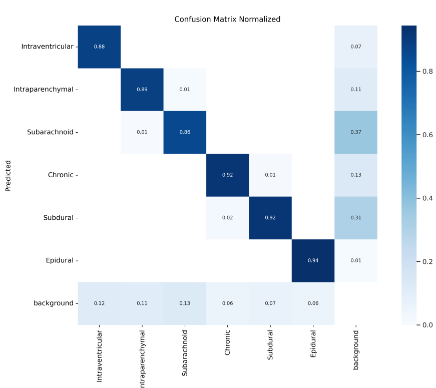


FIGURE 2. Confusion Matrix - Normalized

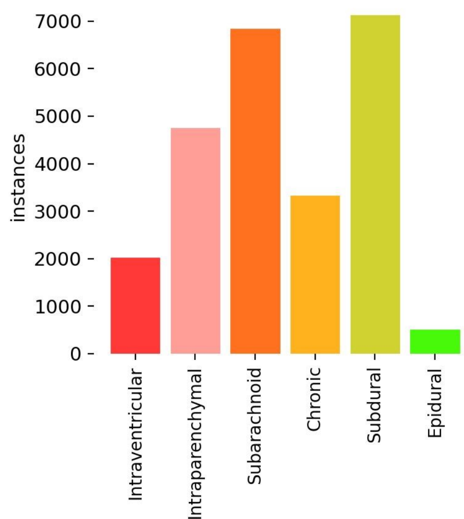
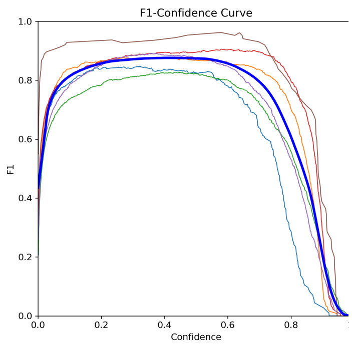
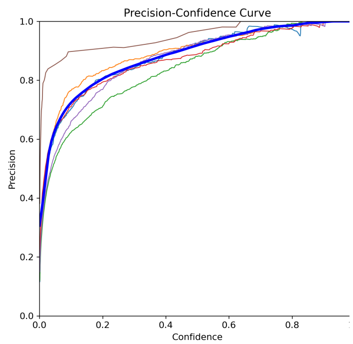


FIGURE 3. Count of different types of labels

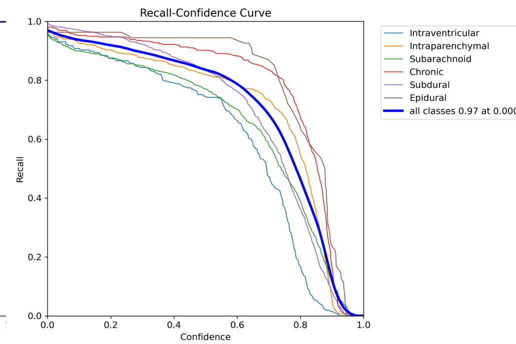
Normalised confusion matrix is a variation used to better understand the classification results. it provides a clearer picture of class-specific performance, helps identify areas where the model might be underperforming, as we can see even though the true positive accuracy according to the confusion matrix is performing better, false positive prediction as background in subarachnoid and in Subdural is significantly high. Better results are expected by training the model for higher number of epochs.



(A) F1 Curve



(B) P Curve



(C) R Curve

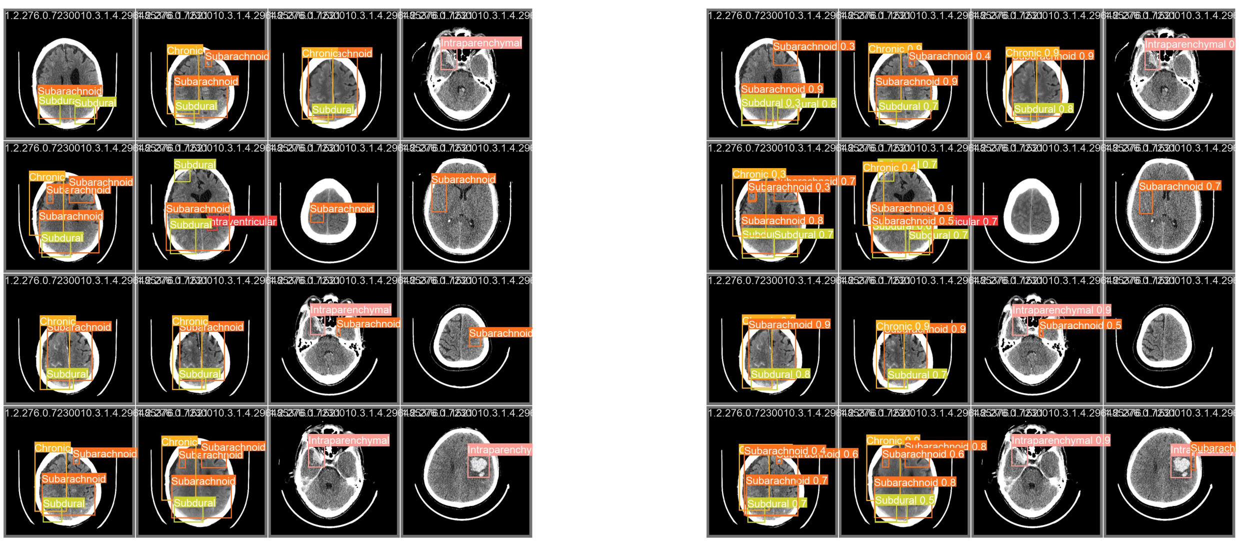


FIGURE 5. True Labels vs Results Comparison - Batch 1

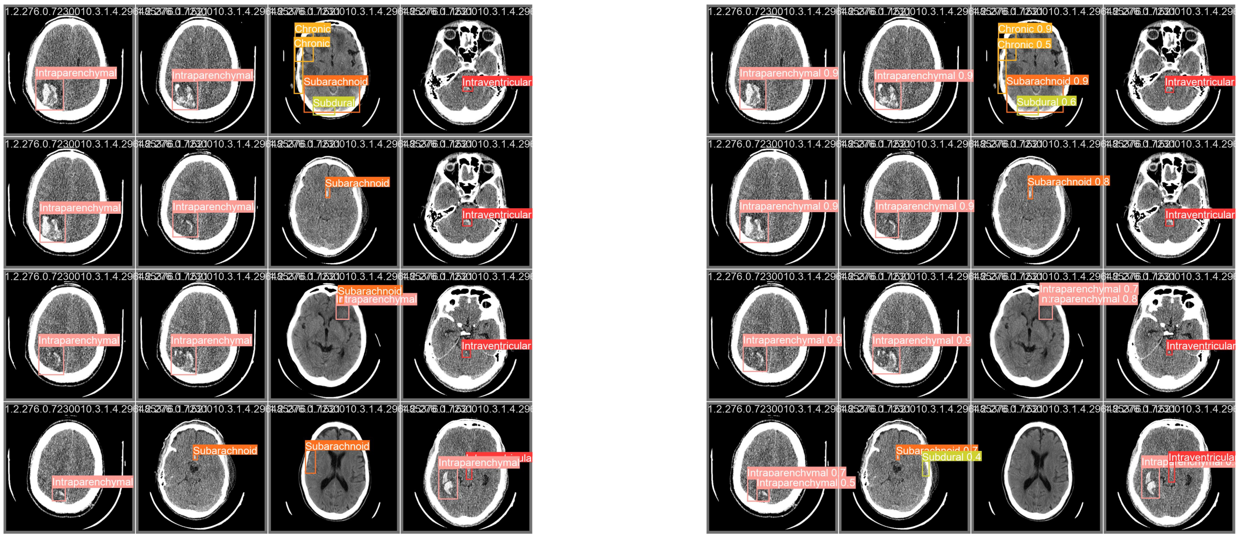


FIGURE 6. True Labels vs Results Comparison - Batch 2

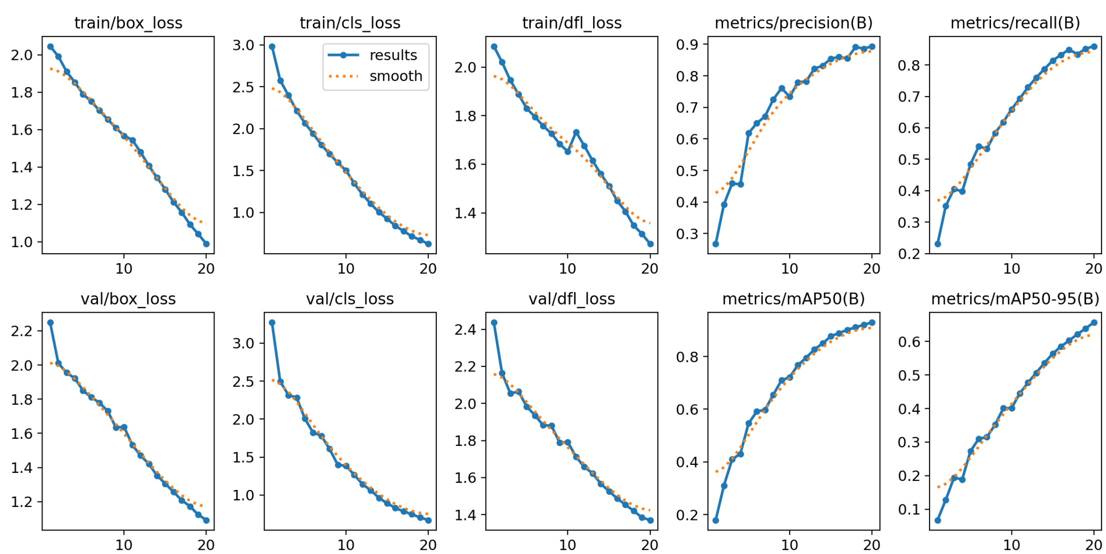


FIGURE 7. Results

5. Future Works

(1) User Interface for Image Input and Treatment Suggestions: This interface would make it easy for users to upload medical images and get results like those produced by the model. Additionally, the interface could offer treatment suggestions based on the model's findings, simplifying decision-making for medical experts and improving patient care

(2) Refining Bounding Box Extrapolation: Some resources acknowledge [4] a limitation related to occasional discrepancies in bounding box coordinates when

extrapolating from thicker to thinner image series. Not other than a neuroradiologist's spot-checking, the automatic bounding boxes cannot be corrected. Future developments could work on this limitation by implementing a refined process.

(3) Expanding the Classification Spectrum: The existing model focuses on detecting and classifying six types of acute intracranial hemorrhage. Future endeavors might broaden the spectrum of classifications to encompass a wider range of cerebral conditions, contributing to more comprehensive diagnosis and treatment plans.

(4) Cross-Modality Image Analysis: As an extension, future work could explore cross-modality image analysis, incorporating not only CT scans but also other neuroimaging modalities like MRI. This cross-modality approach would offer a more comprehensive view of intracranial conditions, further enhancing diagnostic capabilities.

6. Conclusion

Overall, this project demonstrates the potential of YOLOv8 for detecting and localizing intracranial hemorrhage types in clinical practice. With further development and refinement, this approach could lead to improved diagnostic accuracy and timely patient management. This could be implemented for other areas in healthcare development as well.

7. Acknowledgement

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References

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