Intercranial Hemorrhage Detection

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Overview

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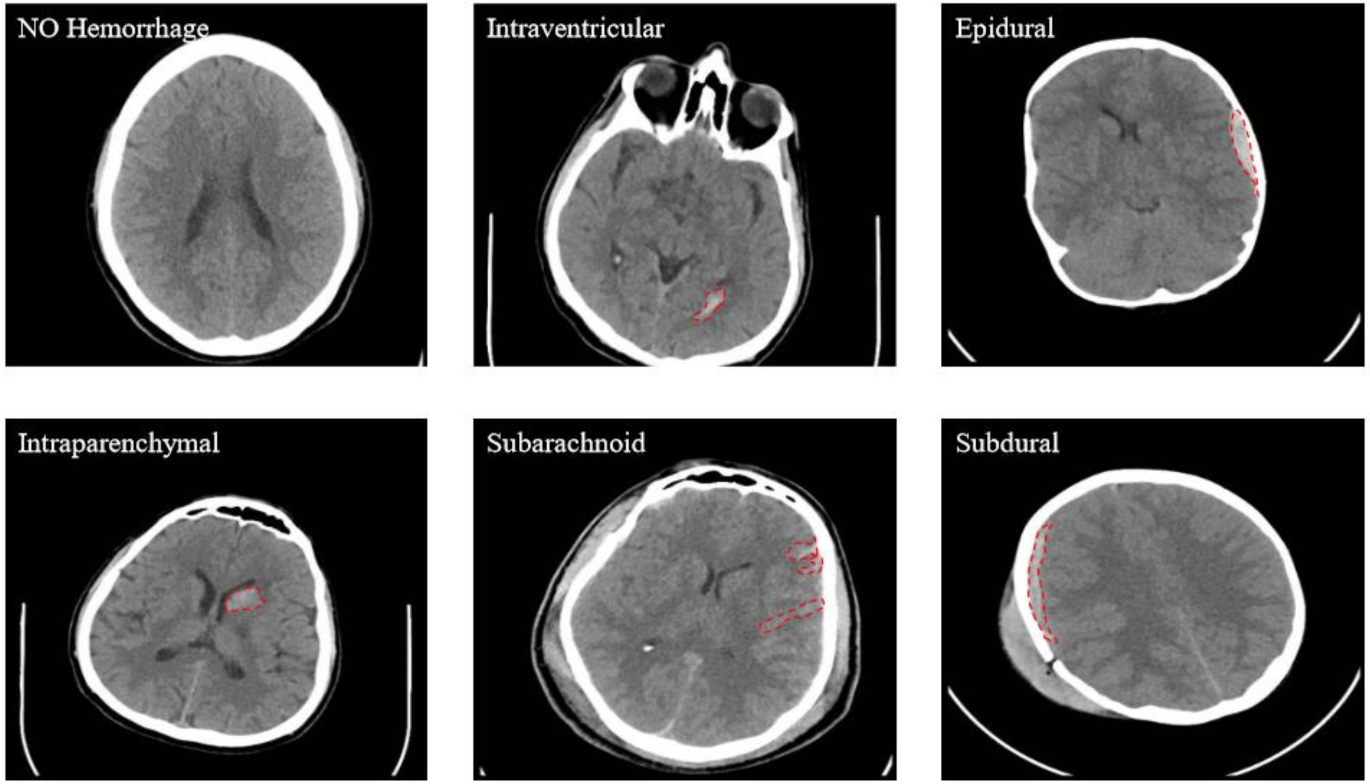
Introduction

What is intracranial hemorrhage?

What are the current methods used to detect it ?

Motivation behind this project and how machine learning can help to improve it

Types of Intracranial Hemorrhage



The Dataset and Machine Learning Model

- Dataset sourced from Kaggle with 2501 CT images for 82 patients, and 318 mask images for the hemorrhage segmentations

- 36 patients had intracranial hemorrhage while 46 did not

- Two machine learning models were used: UNET and Deeplabv3

UNET and Deeplabv3 are effective in identifying subtle changes in medical images. Aimed to improve accuracy and speed of hemorrhage detection in medical imaging scans

Preprocessing and Data Augmentation

Preprocessing:

- Resize
- Crop
- Normalize
- Reshape
- Histogram equalizer
- Contrast stretching

Data Augmentation:

Offline :

- Rotation
- Scaling
- Flipping

Online :

- Rotation
- Width shift
- Height shift
- Shear range
- Zoom
- Horizontal flip
- Fill mode nearest

Training and Testing the Model

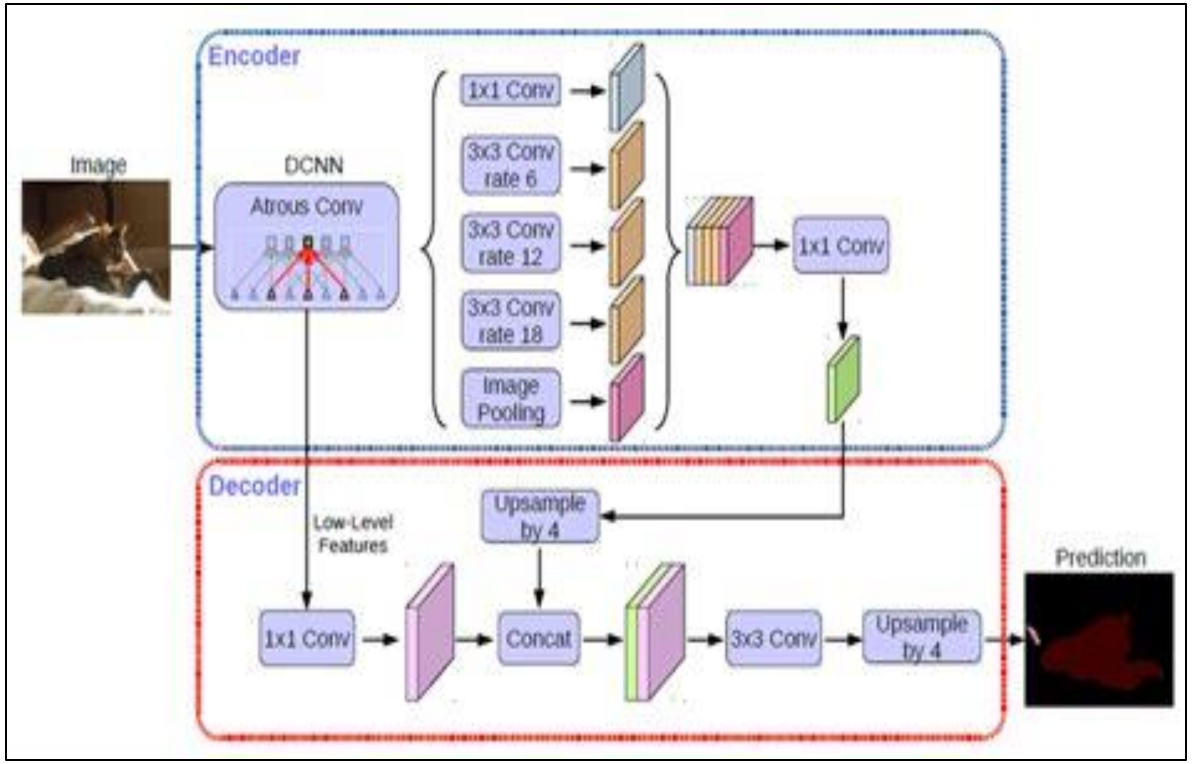
- Concatenated grayscale images and augmented hemorrhage images into X array
- Concatenated masks and augmented masks into y array
- Applied image processing techniques to enhance image quality
- Converted y training data to binary using Otsu's method
- Split data into training and testing sets with an 80/20 split
- Split train set into validation sets with 80/20 split
- Checked shapes of train, test, and validation sets to ensure they are ready for machine learning model

Model Evaluation

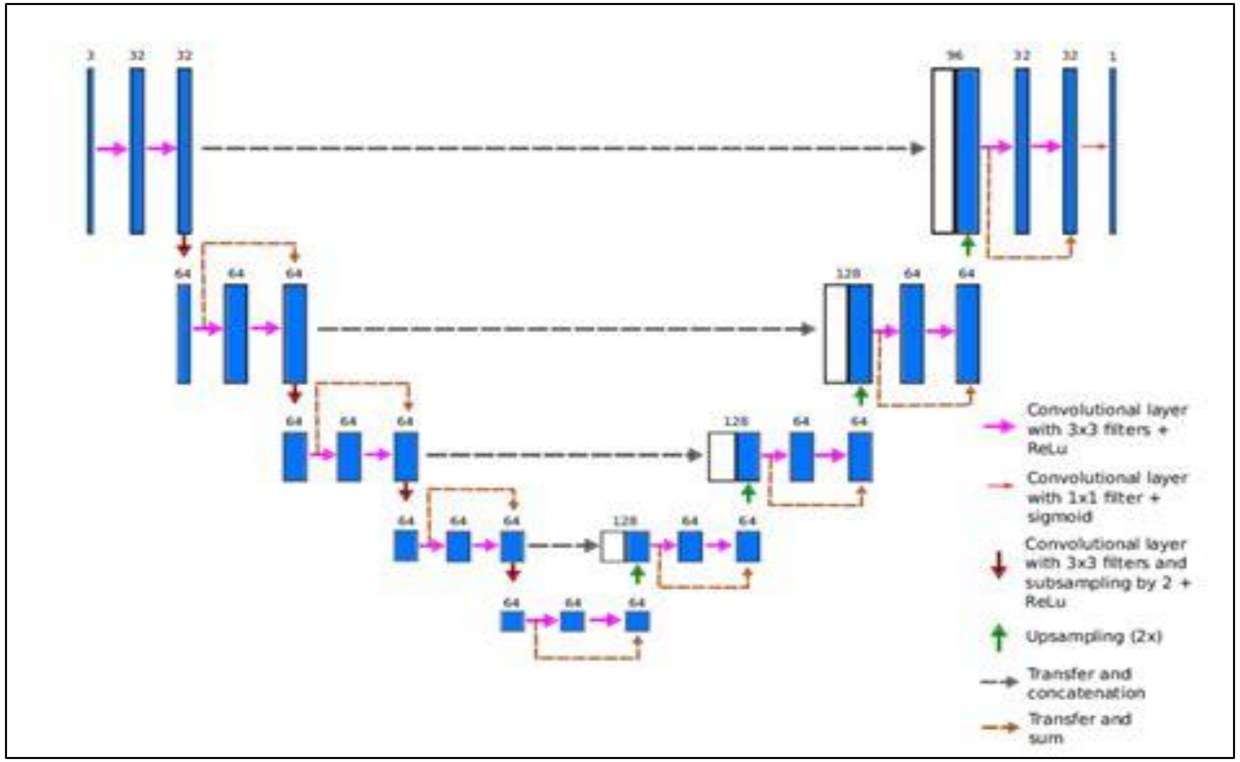
- The first model is a U-Net architecture with 4 levels of convolutional layers and 4 levels of upsampling.
- The model achieved high AUC score of 0.94, but low IoU score of 0.32, indicating difficulty in accurately segmenting the object of interest.
- The second model is a DeepLab architecture with two branches and achieved high AUC and IoU scores of 0.98 and 0.56, respectively.
- The model had good overall performance with high precision and recall for both classes and an accuracy of 0.9978.
- Intracranial hemorrhage binary segmentation is valuable for clinical settings and the success of these models demonstrate the potential of machine learning for accurate and efficient segmentation.
- Further research is needed to evaluate the effectiveness of these models in larger datasets and different clinical settings.

Model architecture

Deeplabv3

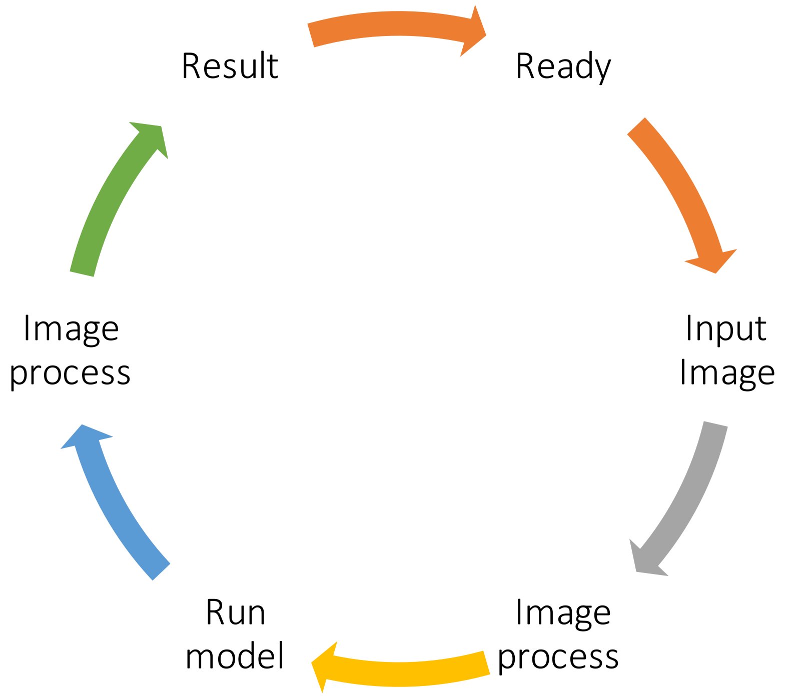


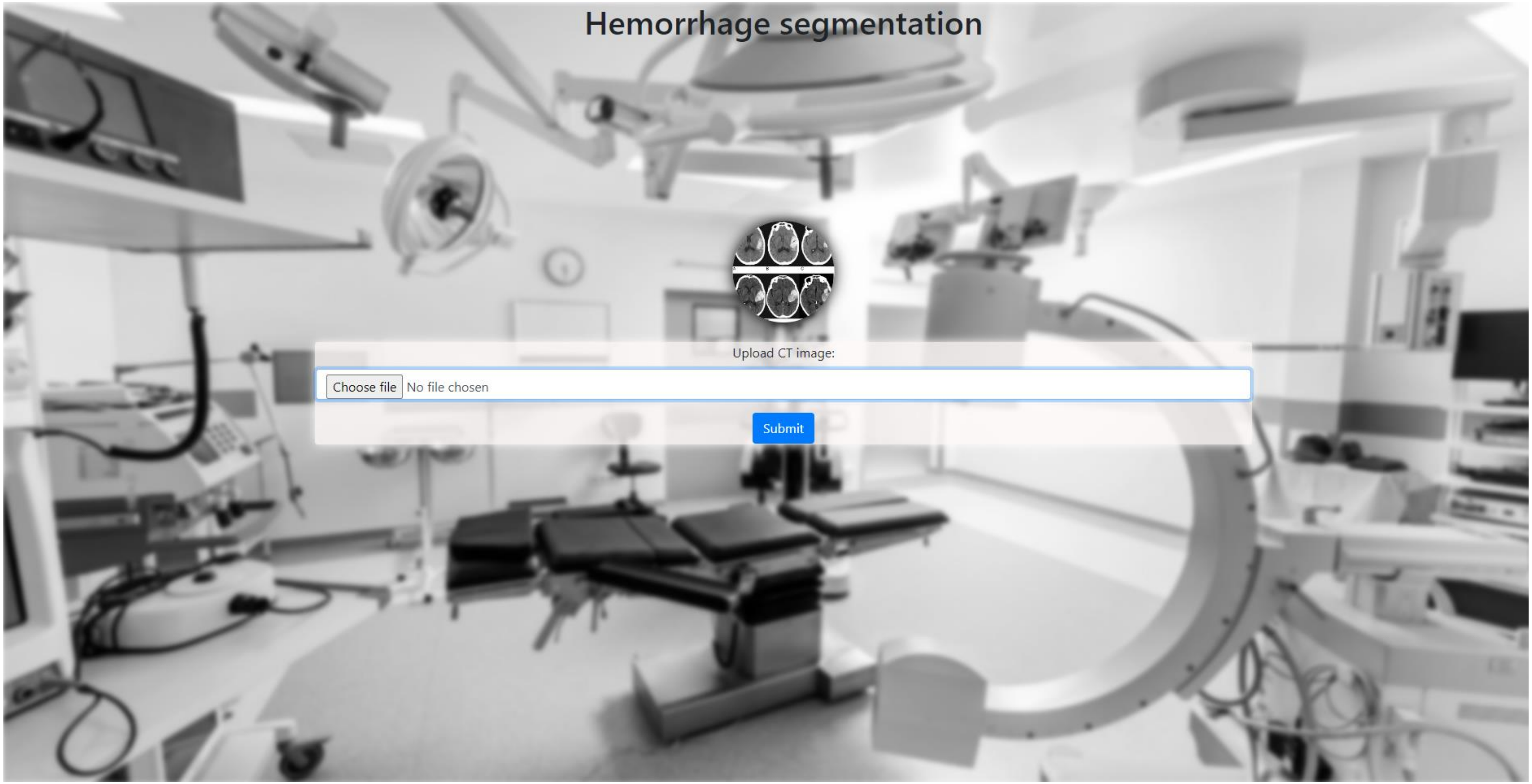
UNET

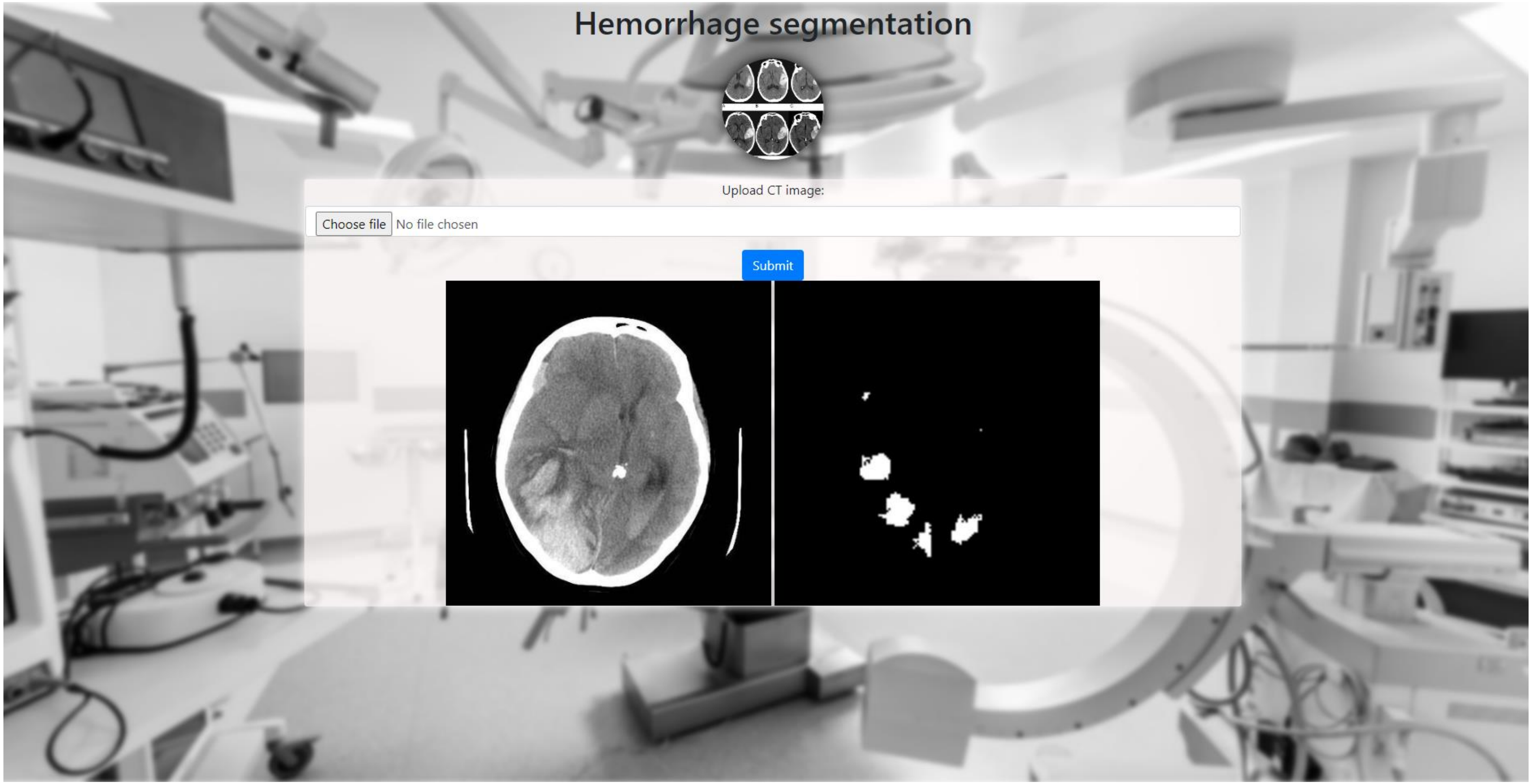


Model Deployment

- The project uses Flask to create a web application
- Components include app.py, main.html, model.py and weights.h5
- After giving an image as input, image segmentation is displayed on the web using Flask and enhanced with HTML, JavaScript, CSS, and Python scripts




Hemorrhage segmentation
Upload CT image:
Choose file
No file chosen
Submit


Hemorrhage segmentation
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Choose file
No file chosen
Submit

Results and Discussions

Model	Precision (Class 0)	Recall (Class 0)	F1-Score (Class 0)	Precision (Class 1)	Recall (Class 1)	F1-Score (Class 1)	AUC	IOU
Deeplabv3	1.00	1.00	1.00	0.93	0.76	0.84	0.98	0.56
UNET	1.00	0.99	0.99	0.38	0.67	0.49	0.98	0.32

Discussion:

•While both U-Net and DeepLab achieved high performance in binary segmentation of intracranial hemorrhage, there is still a need for further research to evaluate their effectiveness in larger datasets and different clinical settings.

•The high precision and recall of the models for the negative class suggest that they can be useful in ruling out the presence of hemorrhage, but their lower precision and recall for the positive class suggest that they may benefit from further improvement in correctly identifying hemorrhages.

•The success of machine learning techniques in accurately and efficiently segmenting medical images for intracranial hemorrhage binary segmentation demonstrates their potential as valuable tools in clinical settings for improving patient outcomes.

Future Directions

- handling different types of medical images such as MRI scans.
- detect the type and cause of hemorrhages
- can be improved with larger and more diverse datasets and advanced deep learning techniques.

Motivation

It is important for developers and researchers to use technology for the benefit of humanity and make progress in improving the quality of healthcare and life globally.

Not only compete to have the best model to make the most profit or to make life and work easier there are more for it.

This project is a simple example to demonstrates the potential for machine learning to improve healthcare and save human lives.