AUTOMATIC BRAIN HEMORRHAGE SEGMENTATION USING 3D DEEP LEARNING MODEL

A PROJECT REPORT

Submitted by

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BONAFIDE CERTIFICATE

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ABSTRACT

This project focuses on the automatic segmentation of brain hemorrhages using a 3D deep learning model. Brain hemorrhages are life-threatening medical emergencies that require precise and timely diagnosis for effective treatment. Current practices for hemorrhage detection primarily rely on manual analysis of 3D CT scans by radiologists, which is time-intensive and prone to variability. Existing automated approaches for brain hemorrhage detection and segmentation often use 2D image processing techniques, which may fail to capture the spatial and volumetric context of hemorrhages in 3D CT scans, leading to suboptimal performance.

The proposed system employs a 3D U-Net deep learning model with a patch-based approach for precise segmentation of brain hemorrhages. By leveraging the volumetric nature of CT data, the system aims to improve the accuracy of hemorrhage detection and delineation. The model is trained on a labeled dataset of 3D CT scans and demonstrating high precision in segmentation. The project also integrates pre-processing steps, including normalization and patch extraction, to optimize the models performance.

Phase I of the project successfully established the groundwork by preparing and pre-processing the dataset, along with implementing the 3D U-Net architecture. Preliminary experiments indicate promising results in terms of segmentation accuracy and robustness.

திட்டப்பணி சுருக்கம்

இந்த திட்டம் மூலமாக மூளையில் இரத்தக்கசிவுகளை தானியங்கி முறையில் பிரித்து காட்சிப்படுத்த 3D ஆழ்ந்த கற்றல் மாடலை (3D Deep Learning Model) பயன்படுத்துகிறது. மூளையில் இரத்தக்கசிவுகள் வாழ்வுக்கு ஆபத்தான மருத்துவ அவசர நிலைமைகள் ஆகும், மேலும் சரியான மற்றும் நேர்மையான கண்டறிதல் தகுந்த சிகிச்சைக்குத் தேவையானவை. தற்போது இந்த கண்டறிதல் முறைகள் மூலமாக 3D CT ஸ்கான்களை கைகொண்டு மறுபரிசீலனை செய்யப்படுகின்றன, ஆனால் இது நேரம் கேட்கும் மற்றும் மாறுபாட்டிற்கு உட்பட்டதாகும். இன்றைய தானியங்கி முறைகள் பெரும்பாலும் 2D பட செயலாக்க நுட்பங்களை பயன்படுத்துகின்றன, இதனால் 3D CT ஸ்கான்களில் இடத்தையும் மொத்த அளவையும் சரியாகப் புரிந்து கொள்ள முடியாமல் குறைந்த செயல்திறனை விளைவிக்கிறது.

இந்த திட்டத்தில் **3D U-Net ஆழ்ந்த கற்றல் மாடல்** மற்றும் **patch-based approach** பயன்படுத்தப்படுகிறது, இது மூளையில் இரத்தக்கசிவுகளை துல்லியமாக பிரித்து காட்சிப்படுத்த உதவுகிறது. **CT தரவின் மொத்த பரிமாணத்தை** பயன்படுத்துவதன் மூலம், முறைமையை மேலும் செயல்திறனுடன் மெருகேற்ற முயற்சி செய்யப்பட்டுள்ளது. **3D CT ஸ்கான்களின் குறியிடப்பட்ட தரவுத்தொகுப்பில்** மாடல் பயிற்சியளிக்கப்பட்டு, உயர்ந்த துல்லியத்தை காட்டுகிறது. இதற்கான முன்னோட்ட செயல்பாடுகளில் **பாதுகாப்பு முன்னேற்பாடு**, **சீராக்குதல் (normalization)** மற்றும் **patch extraction** போன்ற முன்னேற்பாடுகள் சேர்க்கப்பட்டுள்ளன.

திட்டத்தின் முதல் கட்டத்தில் தரவுத்தொகுப்பை தயாரித்து முன்னேற்பாடுகள் செய்யப்பட்டன, மேலும் **3D U-Net கட்டமைப்பை செயல்படுத்த** அடிப்படை வேலைகள் வெற்றிகரமாக முடிக்கப்பட்டுள்ளன. தொடக்க முயற்சிகளில் பிரிப்பு துல்லியத்திலும் முறைமையான செயல்திறனிலும் நம்பகத்தன்மை காணப்பட்டது.

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I also wish to express my sincere thanks to the panel members of the Project Review Committee: **Dr. S. SRIDHAR**, Professor, **Dr. G. GEETHA**, Associate Professor, and **Dr. D. NARASHIMAN**, Teaching Fellow, for their insightful feedback, critical evaluation, and thoughtful suggestions during the review sessions, which significantly enhanced the quality of this project.

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LIST OF SYMBOLS AND ABBREVIATIONS

TBI	Traumatic Brain Injury
CT	Computed Tomography
3D	Three Dimensional
nii	Neuroimaging Informatics Technology Initiative
GT	Ground Truth
ResUNet	Residual U-Net
MRI	Medical Resonance Imaging
AttU-Net	Attention U-Net
IoU	intersection Over Union
PESA	Perihematomal Edema Guided Scale Adaptive
R-CNN	Region-based Convolutional Neural Networks
YOLO	You Only Look Once
ICH	Intracranial Hemorrhage
SARA	Scale Adaptive RoI Align
MSSN	multi-scale segmentation network
CNN	Convolutional Neural Network

CHAPTER 1

INTRODUCTION

Traumatic brain injury is a major global health concern, often resulting from accidents, falls, or sports injuries, and is a leading cause of disability and mortality in young adults. A crucial aspect of TBI management is the accurate identification of intracranial hemorrhages, which are categorized based on bleeding locations within the skull.

1.1 OVERVIEW

Brain hemorrhage, also known as intracranial bleeding, is a serious medical condition characterized by the escape of blood from ruptured blood vessels into or around the brain. It is a potentially life-threatening event that requires immediate medical attention due to its ability to damage brain tissues, increase intracranial pressure, and disrupt normal brain function [1]. Brain hemorrhages can result from various causes, including head trauma, high blood pressure, aneurysms, vascular malformations, or blood disorders. The effects of a brain hemorrhage depend on factors such as the location, size, and cause of the bleeding. Common symptoms include sudden severe headaches, nausea, vomiting, loss of consciousness, weakness, vision disturbances, or seizures. If left untreated, a brain hemorrhage can lead to complications such as permanent neurological deficits, coma, or death. Imaging techniques, particularly CT scans, are the gold standard for diagnosing brain hemorrhages due to their speed and accuracy in detecting blood within the cranial cavity [2]. Timely diagnosis and intervention are critical for managing the condition effectively. While treatment options vary based on the underlying cause and severity, they may include surgical procedures, such as decompression or evacuation of the hematoma, and medical management to stabilize the patient and prevent further complications. Early and precise detection of hemorrhage boundaries is critical for determining the extent of damage and guiding effective treatment. Recent advancements in medical imaging and artificial intelligence are paving the way for innovative diagnostic tools [3]. Automated segmentation methods are emerging as promising solutions to enhance diagnostic efficiency and improve patient outcomes.

1.2 DOMAIN APPLICATION ARAES

The automated segmentation of brain hemorrhages using deep learning has diverse and impactful applications, particularly within healthcare and medical imaging. These advancements aim to elevate diagnostic precision, optimize clinical workflows, and significantly enhance patient outcomes. In Radiology and Diagnostic Imaging, automated segmentation systems provide radiologists with consistent, detailed analyses of brain CT scans. By alleviating the challenges of manual interpretation, these tools enhance diagnostic accuracy and minimize the likelihood of human error, particularly in cases involving subtle or complex hemorrhages. In Telemedicine and Remote Healthcare, automated segmentation systems play a crucial role in addressing the challenges faced by remote or underserved regions with limited access to medical specialists. By integrating into telemedicine platforms, these tools ensure timely, accurate evaluations and bridge critical gaps in healthcare delivery. For Research and Medical Training, automated segmentation methods offer standardized and accurate data analyses, supporting advanced research into brain injuries. Additionally, they serve as valuable educational tools for training healthcare professionals in the identification and management of brain hemorrhages.

1.3 OBJECTIVE

The primary objective of this project are as follows

1. To develop an automated segmentation system using a 3D deep learning model for accurately identifying and segmenting intracranial hemorrhages in brain CT scans.
2. To preprocess and optimize brain CT data for improved input quality and ensure robust segmentation of hemorrhage regions.
3. To evaluate the performance of the proposed system by comparing its segmentation results with manual ground truth data, ensuring reliability and clinical applicability.

1.4 PROBLEM STATEMENT

Intracranial hemorrhages caused by traumatic brain injuries are a significant medical challenge due to their life-threatening nature and the need for immediate intervention. Accurate identification and segmentation of hemorrhages in brain CT scans are crucial for effective diagnosis, treatment planning, and surgical interventions. However, traditional diagnostic methods rely on manual interpretation of CT scans by radiologists, which can be time-consuming, prone to human error, and subject to variability in interpretation. Existing automated methods often lack the precision needed to accurately delineate hemorrhage boundaries or fail to fully utilize the 3D nature of CT data, limiting their clinical utility. This underscores the need for a robust, automated solution that can reliably segment brain hemorrhages, reduce diagnostic delays, and support clinicians in delivering timely and effective care to patients.

1.5 MOTIVATION

Traumatic brain injury is a leading cause of death and disability globally, with brain hemorrhages being among the most severe complications. Every year, millions of people suffer from TBI due to road accidents, falls, and other incidents, with brain hemorrhages being responsible for a significant proportion of deaths. Unfortunately, many of these deaths could potentially be avoided if hemorrhages were detected and treated earlier. Delays in identifying these injuries can result in irreversible brain damage or death, with studies indicating that timely intervention can dramatically improve survival rates. Currently, the diagnosis of brain hemorrhages relies on manual analysis of CT scans by radiologists. This process can be slow, subjective, and prone to human error, especially in high-pressure emergency situations where decisions need to be made quickly. In fact, misdiagnosis or delayed detection of brain hemorrhages is responsible for numerous preventable fatalities every year. The need for more reliable, automated methods for detecting and segmenting brain hemorrhages is urgent. This project is motivated by the critical need to develop an automated system capable of detecting and segmenting brain hemorrhages in CT scans with high accuracy and speed. By using deep learning techniques and aim to reduce human error, streamline the diagnostic process, and ultimately save lives. With faster, more reliable detection and hope to reduce the number of people who suffer irreversible brain damage or death due to delayed hemorrhage identification and intervention.

1.6 PROPOSED SOLUTION

This project proposes a 3D Deep learning segmentation model designed to accurately identify and segment intracranial hemorrhages in brain CT scans. The model leverages advanced deep learning techniques, robust preprocessing, and optimized training strategies to enhance segmentation accuracy and clinical applicability.

The CT scans are preprocessed through intensity normalization to ensure high-quality inputs for the model. The proposed 3D U-Net architecture processes volumetric data, extracting spatial and contextual features crucial for precise segmentation. Encoder-decoder structures in the network capture both global context and fine-grained details, with skip connections to retain spatial resolution.

The model is trained using a hybrid loss function combining Dice Loss and Binary Cross-Entropy Loss to address class imbalance and improve segmentation performance. This approach systematically enhances the detection of hemorrhage boundaries by addressing challenges like noise, variability in data, and complex anatomical structures. Extensive evaluation on benchmark datasets demonstrates the model's capability to deliver reliable segmentation results, aligning closely with manual ground truth annotations.

1.7 ORGANIZATION OF THE PROJECT

This report is organized into 6 chapters. First, an introduction is provided, outlining the objectives and scope of the project, followed by describing each part of the project with detailed illustrations and system design diagrams.

Chapter 2: Discusses Literature reviews of existing research, studies, and relevant literature related to brain hemorrage detection and segmentation.

Chapter 3: Discusses the overall system architecture of the entire system and followed by that gives the brief information about technologies that are used in the projects modules.

Chapter 4: Delves into the various algorithms and modules implemented in the project.

Chapter 5: Discusses the result and analysis presents the results of the project, including the performance metrics of the each models.

Chapter 6: Discusses the conclusion and future work, summarizes the findings and conclusions drawn from the project.

CHAPTER 2

LITERATURE SURVEY

This chapter explores the existing work in the field of deep learning techniques applied to brain hemorrhage segmentation. It provides an overview of the challenges and advancements in developing segmentation models, with a focus on methodologies, their effectiveness, and performance in detecting intracranial hemorrhages from medical imaging.

2.1 EXISTING SYSTEM

This section of the literature survey discusses previous methods used for brain hemorrhage detection and segmentation. These methods can be broadly categorized into two main approaches: traditional image processing-based methods and deep learning-based methods. The existing works under these categories are discussed below.

2.1.1 SEGMENTATION METHODS USING MRI DATA

Smarta Sangui et al.[4] explored the use of a 3D U-Net architecture for MRI-based segmentation of brain tumors. The modified U-Net architecture for segmenting brain tumors from 3D MRI images using the BRATS 2020 dataset. The approach effectively addressed the challenges of segmenting complex tumor regions in MRI data by incorporating advanced feature extraction techniques. However, the method's dependency on high computational power and hardware resources limits its accessibility, and its performance heavily relies on preprocessing quality and dataset variability, potentially affecting its generalizability.

In a similar vein, Rahul Roy et al.[5] utilized a 3D Attention U-Net for brain tumor segmentation. The key innovation in this paper is the introduction of attention mechanisms within the U-Net architecture. Applied to the BRATS2020 dataset, the model achieved significant improvements, including a 5% increase in dice coefficient across tumor classes, making it effective for segmenting core, enhancing, and whole tumors. The inclusion of attention mechanisms improved feature learning for better segmentation. Despite its advancements, the model still struggles with accurately segmenting enhanced and core tumors, and its high computational demands present practical challenges. Further research is needed to optimize performance for rare tumor classes.

2.1.2 DEEP LEARNING APPROACH FOR HEMORRHAGE SEGMENTATION

Joonho Chang et al.[6] introduced the PESA R-CNN model, which integrates perihematomal edema to enhance hemorrhage segmentation. PESA R-CNN, designed to enhance segmentation of intracranial hemorrhage by leveraging perihematomal edema as a cue for improved region proposal and segmentation accuracy. The model employs a Center Surround Difference U-Net for weakly supervised PHE estimation and a Scale Adaptive RoI Align to retain fine details in small hemorrhages. The multi-scale segmentation network further addresses size imbalance in RoIs, improving accuracy for hemorrhages of varying sizes. Despite its innovation, the model relies on manually labeled datasets and requires extensive computational resources for training, limiting its scalability in real-time clinical scenarios. Additionally, the weak supervision approach for PHE estimation may not fully capture all edema patterns, potentially affecting segmentation accuracy.

Abdesselam Ferdi et al.[7] proposed a Q-YOLOv8, a novel detector integrating quadratic convolution with YOLOv8 to improve localization of mixed ICH using bounding boxes in CT images. The method enhances feature representation and achieves high localization precision on the BHX dataset. The paper addresses limitations of conventional convolutional layers by incorporating QC for better non-linear feature extraction. However, the approach is limited by its dependence on high-quality annotations and computational requirements for training the quadratic model. The focus on localization rather than segmentation also restricts its application in scenarios demanding precise hemorrhage boundaries.

Jason Walsh et al.[8] introduces a lightweight U-Net architecture for efficient brain tumor segmentation in MRI images, emphasizing real-time application and minimal computational requirements. Unlike traditional methods, which often depend on large datasets and aggressive data augmentation, this approach uses 2D slices from three perspective planescoronal, sagittal, and transversalmaking it more accessible. The proposed model was tested on the BITE dataset and achieved a mean intersection-over-union (IoU) of 89%, outperforming several standard benchmarks. Its ability to provide accurate segmentation with smaller datasets and without extensive preprocessing highlights its practicality for medical applications. However, the reliance on 2D slices limits its capacity to fully utilize 3D volumetric MRI data, and segmentation performance was lower on sagittal and coronal planes, likely due to dataset size and tumor visibility. Additionally, further exploration of data augmentation or 3D segmentation techniques could enhance its performance.

2.1.3 HYBRID MODELS FOR BRAIN HEMORRHAGE DETECTION AND SEGMENTATION

Chang et al.[15] developed a hybrid 3D/2D convolutional neural network for detecting and quantifying intracranial hemorrhages from head CT scans. Their custom mask R-CNN architecture could detect intraparenchymal, epidural/subdural, and subarachnoid hemorrhages while also providing precise volume measurements. The model was trained on over 10,000 CT examinations and validated both retrospectively and prospectively. A key strength was their successful deployment of the algorithm in a real clinical environment through an automated pipeline processing emergency department CT scans. However, limitations included the single-institution nature of their dataset and potential susceptibility to adversarial noise in the deep learning model.

2.2 LITERATURE SURVEY SUMMARY

In the literature survey, several challenges in brain hemorrhage segmentation were highlighted, including the difficulty in detecting subtle hemorrhages, managing low-contrast or noisy images, and addressing the complex anatomical variations in medical scans. Moreover, many existing models struggle with achieving accurate segmentation, especially in cases of traumatic brain injuries. These challenges are exacerbated when working with limited or imbalanced datasets, which can affect the generalizability and performance of the models. Additionally, computational resource requirements and the reliance on high-quality annotations further limit the scalability and real-time applicability of some methods.

2.3 OBJECTIVE OF THE PROPOSED SYSTEM

- To develop an automated segmentation system using a 3D deep learning model to accurately identify and segment intracranial hemorrhages in brain CT scans, addressing challenges such as detecting subtle hemorrhages and handling noisy, low-contrast images.
- To improve input quality and ensure robust segmentation of hemorrhagic regions,To Preprocess and optimize brain CT data, overcoming the difficulty of dealing with complex anatomical variations and dataset limitations.
- To evaluate the performance of the proposed system by comparing its segmentation results with manual ground truth data to ensure reliability and clinical applicability, overcoming challenges related to segmentation accuracy in real-world clinical scenarios.

CHAPTER 3

SYSTEM ARCHITECTURE

This chapter presents the system architecture of the brain hemorrhage segmentation framework. outlining the preprocessing of 3D CT scan data, the implementation of advanced deep learning techniques, and the integration of various modules to achieve accurate and efficient segmentation of intracranial hemorrhages.

3.1 ARCHITECTURE OF THE BRAIN HEMORRHAGE SEGMENTATION MODEL

This system architecture 3.1 outlines a comprehensive framework designed for brain hemorrhage segmentation and analysis. The workflow begins with data preprocessing, which includes splitting the data into train and test sets, patch extraction, and normalization. Segmentation models such as 3D U-Net, 3D ResUNet, and DeepMedic are utilized to detect hemorrhages, followed by model evaluation. Post-processing methods refine the predictions, while visualization provides a clear representation of the results. The best-performing model is chosen based on its performance and evaluation metrics. To ensure robustness, various performance metrics like Dice Similarity Coefficient, Precision and recall are used to assess the quality of the segmentation. The final model is selected based on a balance between high dice coefficient and sensitivity, ensuring both accurate detection and minimal false positives.

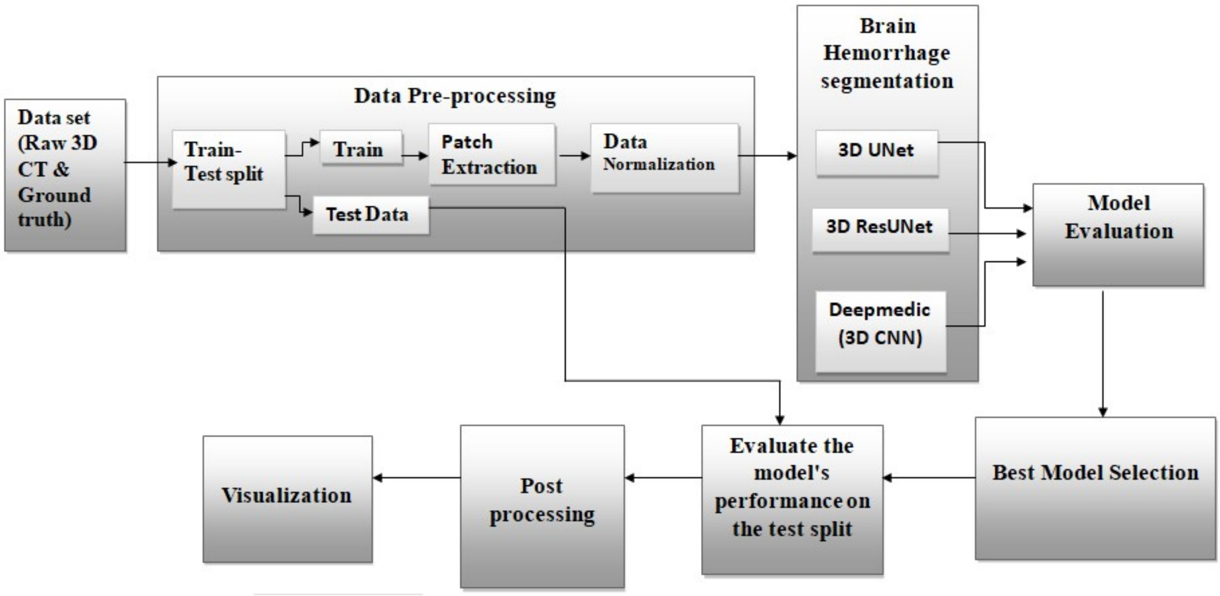

Figure 3.1: Architecture Diagram of Brain Hemorrhage segmentation

3.2 DATA COLLECTION

The dataset used in this project is obtained from the MBH-Seg: Brain Hemorrhage Segmentation in Non-contrast CT dataset. This dataset is specifically designed for the segmentation of intracranial hemorrhages in non-contrast CT scans, making it highly suitable for the objectives of this project.The dataset contains a total of 192 CT scans, provided in the standard Neuroimaging Informatics Technology Initiative (`.nii`) format. Each CT scan is accompanied by its respective ground truth segmentation file, also in `.nii` format, which serves as the reference standard for training and evaluating the segmentation model.

3.3 DATA PRE-PROCESSING

Data preprocessing is a crucial step in preparing the dataset for effective training and evaluation of the deep learning model. The raw CT scan data and ground truth segmentations in the .nii format are processed to ensure consistency, enhance quality, and optimize the model's performance.

3.3.1 DATASET ORGANIZATION

The original CT scans and their respective ground truth segmentation files are divided into training and testing sets, maintaining an 80-20 split. These splits are stored in dedicated directories to ensure clear separation between the data used for model learning and evaluation. Each CT scan and its corresponding ground truth are carefully paired to avoid mismatches during processing. This structured organization provides a strong foundation for subsequent steps in the preprocessing pipeline.

3.3.2 NORMALIZATION

The image is normalized to a [0, 1] range by subtracting the minimum intensity value and dividing by the intensity range. This process standardizes the image intensities, making them consistent for better model training and convergence.

3.3.3 PATCH EXTRACTION

To handle the high dimensionality of 3D CT scans effectively, the data is segmented into smaller, manageable patches of uniform size (16x32x32) 3.2. Hemorrhage patches are identified and extracted based on the ground truth segmentation maps, ensuring a minimum percentage of hemorrhage presence in the patches. Additionally, care is taken to focus on the central regions of patches to avoid edge noise and enhance the quality of extracted information. For normal patches, regions devoid of hemorrhage are sampled, ensuring that they are sufficiently far from hemorrhage areas to maintain class distinction. This step is crucial in creating a balanced dataset for model training, improving the ability to distinguish between hemorrhage and normal regions.

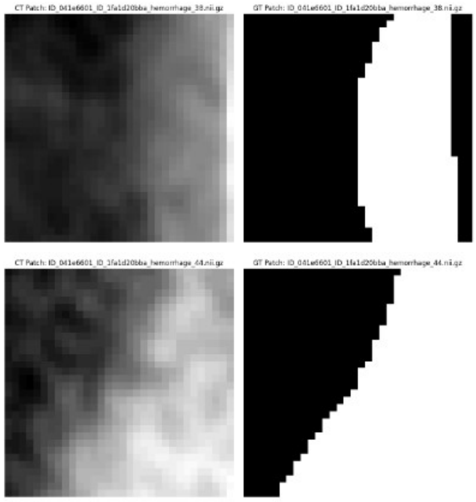

Figure 3.2: Extracted Hemorrhage Patches

3.4 BRAIN HEMORRHAGE SEGMENTATION MODELS

Segmentation model is a type of deep learning model used to divide an image into different regions or segments, each representing a specific object or class. It assigns a label to each pixel in an image, allowing for precise localization of features or structures. Here is a brief overview of the models you're using for 3D medical image segmentation:

1. **3D U-Net:** The 3D U-Net is an extension of the 2D U-Net architecture designed for 3D volumetric data. It consists of an encoder-decoder structure with skip connections to capture both global and local features. It effectively handles 3D data and preserves spatial information, making it ideal for medical imaging tasks.

2. **3D ResU-Net:** The 3D ResU-Net combines the strengths of 3D U-Net and residual connections. The addition of residual blocks

helps mitigate the vanishing gradient problem, improving the models ability to learn deep features and achieve better performance in complex segmentation tasks.

3. **DeepMedic:** DeepMedic is a deep learning architecture designed specifically for multi-scale brain tumor segmentation. It employs a multi-channel convolutional network with two paths: one for local spatial features and another for global context. It uses 3D convolutions to capture local spatial information effectively.

The selection of the best model for segmentation is based on performance metrics, and in this case, 3D U-Net emerges as the top-performing model.

3.4.1 3D U-NET

The 3D U-Net architecture 3.3 consists of two main components: the Encoder and the Decoder, with a Bottleneck layer that connects them. The Encoder extracts low-level and high-level features from the input image, while the Decoder utilizes these features to reconstruct the segmentation map. The network is designed with several key characteristics to improve performance, including batch normalization, dropout for regularization, and skip connections to preserve fine-grained details in the output.

Encoder: The encoder progressively reduces the spatial dimensions of the input data through successive convolutional layers followed by max-pooling layers. In each convolutional block, two 3D convolutional layers are followed by batch normalization and ReLU activation. Dropout layers are introduced after pooling layers to reduce overfitting, and the number of filters increases with each successive block to capture higher-level features. The encoder learns hierarchical features from the input image at various scales,

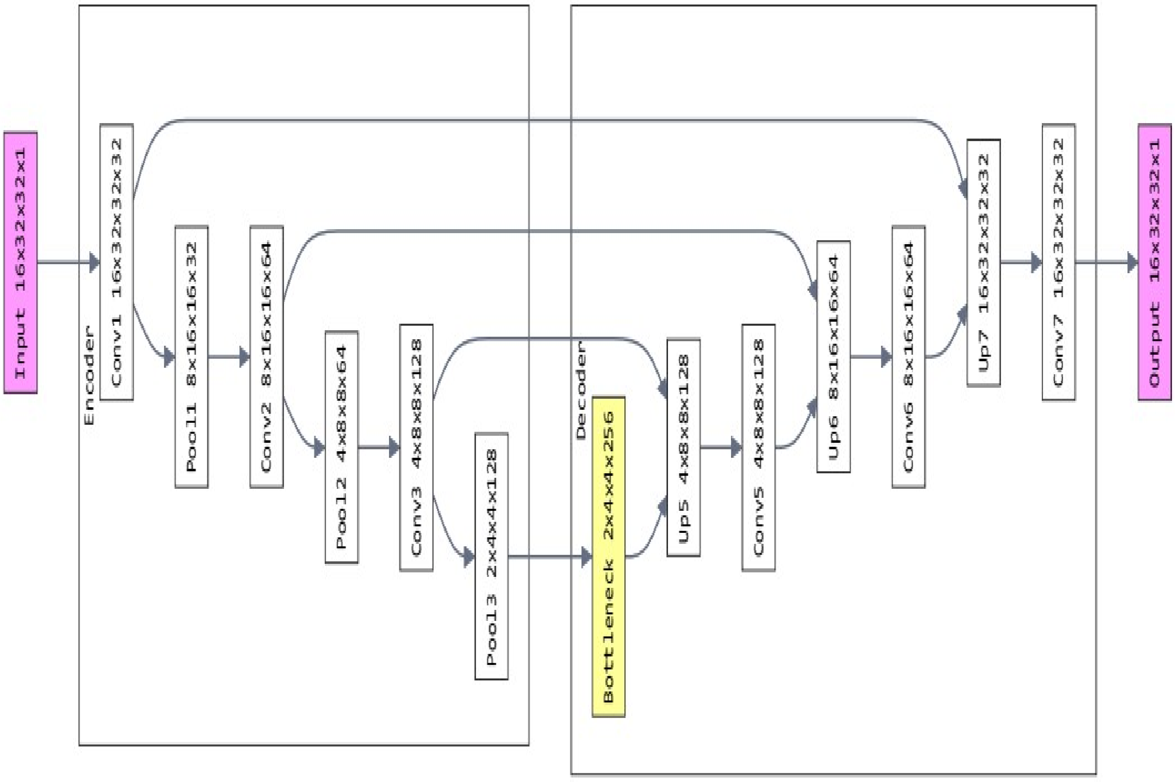

Figure 3.3: 3D U-Net Architecture

enhancing the model's ability to segment complex structures in 3D medical images.

Bottleneck: At the bottleneck layer, the network extracts the most abstract and high-level features by applying two 3D convolutional layers with increased filter sizes. Batch normalization is used to stabilize training, and ReLU activation functions are applied for non-linearity. Dropout is applied here to prevent overfitting, particularly given the complex nature of medical image data.

Decoder: The decoder reconstructs the segmented output by using upsampling operations, implemented with 3D transposed convolutional layers also known as deconvolution. These layers effectively "undo" the downsampling performed in the encoder, restoring the image's original size while leveraging the features learned by the encoder. Skip connections are used to concatenate the upsampled features with the corresponding features from the encoder. This fusion of features from different levels of abstraction helps the model retain fine details necessary for precise segmentation.

Output Layer: The output layer consists of a single 3D convolutional layer with a sigmoid activation function, producing a binary mask that indicates the presence or absence of the target structure, hemorrhage in CT scans.

3.5 MODEL EVALUATION

Model evaluation is a critical step in determining the effectiveness of a deep learning architecture in solving the segmentation task. In this study, the performance of various models was compared based on a range of evaluation metrics to identify the best-performing model for brain hemorrhage segmentation. The models tested include 3D U-Net, 3D ResUNet, and DeepMedic, each offering different architectural strengths and complexities. To objectively evaluate and compare the performance of these models, several metrics includes accuracy, dice coefficient, precision and recall.

3.6 POST PROCESSING AND VISUALIZATION

After selecting the best-performing model based on evaluation metrics, the test data was used to generate predictions. Post-processing refines the raw predictions from the model to produce accurate and clinically meaningful results. The key steps include binarization to convert predictions into binary masks, morphological operations to smooth boundaries, removal of small isolated components to reduce noise, and patch reconstruction to combine overlapping predictions into a full 3D volume. These steps ensure the output is clean, and ready for visualization or further analysis. To evaluate the effectiveness of post-processing, the predictions were visualized alongside the original CT scans and the ground truth masks.

3.7 SUMMARY

This chapter presents the system architecture for brain hemorrhage segmentation, beginning with data preprocessing, including dataset splitting, patch extraction, and normalization. Segmentation models such as 3D U-Net, 3D ResUNet, and DeepMedic are applied to detect hemorrhages. Following model evaluation, post-processing methods refine the predictions, which are then visualized for clear representation. The overall architecture is designed to ensure an effective workflow, optimizing each step to enhance the segmentation process's accuracy and quality.

CHAPTER 4

DESIGN AND IMPLEMENTATION

This chapter describes the system's implementation and the technologies used, including the definition of the underlying logic.

4.1 BRAIN HEMORRHAGE SEGMENTATION USING 3D U-NET

In this project, a 3D U-Net model is utilized for brain hemorrhage segmentation from CT scans, focusing on leveraging the spatial context inherent in 3D medical data. The model processes 3D patches of size $16 \times 32 \times 32$, extracted from both the CT images and their corresponding ground truth masks. This patch-based approach enables the model to efficiently learn features at multiple scales while capturing intricate spatial relationships within the brain. By working with smaller sub-volumes, the model reduces computational complexity and enhances data augmentation through overlapping patches. The 3D U-Nets encoder-decoder architecture, combined with skip connections, ensures accurate segmentation by preserving critical spatial and contextual information. This design allows the model to effectively identify hemorrhagic regions, even in noisy or low-contrast images, while maintaining the brain's structural integrity.

4.1.1 PRE-PROCESSING

Algorithm 4.1 Preprocessing and Normalization

Input: 3D CT Image, Ground Truth Image
Output: Normalized CT Image, Binary GT Image

1. **function PREPROCESSING_AND_NORMALIZATION**(ct_image, gt_image)
2. **LOAD** CT image and corresponding GT image
3. **NORMALIZE** CT image (clip values and apply min-max normalization)
4. **CONVERT** GT image to binary format (hemorrhage = 1, other regions = 0)
5. **RETURN** normalized CT image and binary GT image
6. **end function**

Explanation:

In this algorithm, the goal is to preprocess the input CT and ground truth images before patch extraction. The process begins by loading the CT and GT images from their respective file paths. Once the images are loaded, the CT image undergoes normalization. This step may involve clipping intensity values and applying min-max normalization to ensure that the CT image has consistent intensity values, which is crucial for improving model training. The ground truth image, is converted into a binary format, marking hemorrhage regions with a value of 1 and the rest of the regions with a value of 0. The output of this algorithm is the preprocessed CT image and the binary GT image, both of which are ready for subsequent patch extraction.

4.1.2 HEMORRHAGE PATCH EXTRACTION

Algorithm 4.2 Hemorrhage Patch Extraction

Input: Normalized CT Image, Binary GT Image, Patch Size, Valid Ranges
Output: Valid Hemorrhage Patches

1. **function HEMORRHAGE_PATCH_EXTRACTION**(ct_image, gt_image, patch_size, valid_ranges)
2. **SET** *patch depth, height, and width* from *patch_size*
3. **FOR** each possible patch position (z, y, x) within the valid ranges:
4. **EXTRACT** the patch from the GT image at position (z, y, x)
5. **VALIDATE** the patch using hemorrhage percentage and distribution criteria
6. IF the patch is valid, calculate the centroid of hemorrhage pixels
7. **ADJUST** the patch position to center the hemorrhage
8. **STORE** valid hemorrhage patch positions
9. **END FOR**
10. **RETURN** list of valid hemorrhage patch positions
11. **end function**

Explanation:

The purpose of this algorithm is to extract patches from the CT and ground truth images that contain hemorrhages. The algorithm starts by setting the patch size according to the input parameters. It then iterates over all possible patch positions within the valid range of the image. For each potential patch, both the CT image and the corresponding GT image are loaded. Next, the algorithm checks if the selected patch contains hemorrhage using specific criteria, such as the percentage of hemorrhage pixels in the patch. It also ensures that hemorrhage regions are not merely located at the edges but are well-distributed within the patch. If the patch meets these criteria, the algorithm calculates the centroid of the hemorrhage and adjusts the patch position to center the hemorrhage. The valid hemorrhage patches are then stored and returned.

4.1.3 NON HEMORRHAGE PATCH EXTRACTION

Algorithm 4.3 Normal Patch Extraction

Input: Normalized CT Image, Binary GT Image, Hemorrhage Positions, Patch Size, Valid Ranges, Patches per Class
Output: Valid Normal Patches

1. **function NORMAL_PATCH_EXTRACTION**(ct_image, gt_image, hemorrhage_positions, patch_size, valid_ranges, patches_per_class)
2. **CREATE** hemorrhage distance map highlighting hemorrhage regions
3. **SET** *patch depth, height, and width* from *patch_size*
4. **SET** *valid ranges* for depth, height, and width from *valid_ranges*
5. **FOR** each possible patch position (z, y, x) within the valid ranges:
6. **RANDOMLY SELECT** patch positions that are far from hemorrhage regions (using the distance map)
7. **EXTRACT** patch from GT image at (z, y, x)
8. **IF** patch contains no hemorrhage (all zeros), consider it a valid normal patch
9. **ADD** the patch to normal patch list if valid
10. **STOP** if the required number of normal patches is found (patches_per_class)
11. **END FOR**
12. **RETURN** list of valid normal patch positions
13. **end function**

Explanation:

This algorithm aims to extract patches that do not contain any hemorrhage. It first generates a hemorrhage distance map, which identifies regions in the image that are far from the hemorrhage areas. The patch size is defined, and the algorithm iterates over all possible patch positions within the valid ranges. For each potential position, it checks if the patch is sufficiently far from any hemorrhage. If the patch does not overlap with hemorrhage regions, it is considered a valid normal patch. The algorithm continues this process until the specified number of normal patches has been extracted.

4.2 3D U-NET FOR SEGMENTATION

Algorithm 4.4 3D U-Net Architecture for Segmentation

Input: Patch Size ($input\_shape$), Filters ($n\_filters$), Dropout Rates ($dropout\_rates$), Learning Rate (lr)
Output: 3D U-Net Model
Steps:

1. **Encoder:** For each block:
   (a) Apply two $3 \times 3 \times 3$ convolutions, batch normalization, ReLU, and dropout ($dropout\_rates[i]$).
   (b) Perform $2 \times 2 \times 2$ max pooling. Double filters for next block.
2. **Bottleneck:**
   (a) Apply two $3 \times 3 \times 3$ convolutions with $n\_filters$, batch normalization, ReLU, and dropout.
3. **Decoder:** For each block:
   (a) Perform $2 \times 2 \times 2$ transposed convolution for upsampling.
   (b) Concatenate with corresponding encoder features.
   (c) Apply two $3 \times 3 \times 3$ convolutions, batch normalization, ReLU, and dropout.
   (d) Halve filters for next block.
4. **Output:** Add $1 \times 1 \times 1$ convolution with sigmoid activation.

Explanation:

The 3D U-Net architecture is designed for volumetric data segmentation, making it ideal for tasks like medical imaging. It begins with an input layer shaped to match the patch size of the 3D input data. The encoder path consists of repeated convolutional blocks, each performing two 3D convolutions followed by batch normalization and ReLU activation to extract spatial features. Max pooling layers reduce spatial dimensions, while dropout layers enhance regularization. The bottleneck layer at the center applies deeper convolutions for high-level feature extraction. The decoder path mirrors the encoder, using transposed convolutions for upsampling and skip connections to integrate encoder features, preserving spatial details. Finally, a $1 \times 1 \times 1$ convolution with a sigmoid activation generates the segmentation mask.

4.3 POST PROCESSING

Algorithm 4.5 Post-Processing of 3D Segmentation Predictions

Input: Prediction Volume (*prediction*), Minimum Component Size (*min_size*)
Output: Cleaned Binary Prediction Volume (*binary_pred*)
Steps:

1. **Thresholding:**
   (a) Convert the soft prediction to a binary mask:
   $$binary\_pred \leftarrow prediction > 0.5$$
2. **Connected Component Analysis:**
   (a) Label connected components in the binary mask:
   $$labeled\_array, num\_features \leftarrow label(binary\_pred)$$
   (b) Compute the size of each connected component:
   $$component\_sizes \leftarrow bincount(labeled\_array.ravel())$$
3. **Morphological Closing:**
   (a) Apply morphological closing to smooth boundaries:
   $$binary\_pred \leftarrow binary\_closing(binary\_pred)$$
4. **Convert to Unsigned Integer:**
   (a) Convert the final binary mask to an unsigned 8-bit integer:
   $$binary\_pred \leftarrow binary\_pred.astype(uint8)$$

Return: Cleaned Binary Prediction Volume (*binary_pred*)

Explanation:

The post-processing algorithm refines 3D segmentation predictions to enhance accuracy and remove noise. It begins by thresholding the soft predictions to create a binary mask. Connected components in this mask are labeled, and their sizes are computed. Morphological closing is applied to smooth the boundaries of the remaining regions. Finally, the cleaned binary mask is converted to an unsigned integer format for compatibility, resulting in a refined segmentation output suitable for analysis or visualization. These steps ensure the removal of spurious regions while preserving meaningful structures. The refined output significantly improves the reliability of subsequent clinical or computational analyses.

4.4 SUMMARY

This chapter outlines a series of algorithms for preprocessing, patch extraction, and post-processing in the context of 3D medical image segmentation, specifically for hemorrhage detection. It begins with preprocessing the CT and ground truth images, normalizing the CT image and converting the ground truth to a binary format. The next step involves extracting hemorrhage patches based on specific criteria, followed by extracting normal patches away from hemorrhage areas. The 3D U-Net model is then employed for segmentation, which includes an encoder-decoder architecture with convolutional layers, batch normalization, and dropout for regularization. Finally, post-processing techniques such as thresholding, connected component analysis, and morphological closing are applied to refine the segmentation results. The chapter provides a detailed framework for preparing data, training a segmentation model, and improving the quality of predictions.

CHAPTER 5

RESULTS AND ANALYSIS

In this section, the results of the brain hemorrhage segmentation model are presented, along with an analysis of its performance across several key metrics.

5.1 EVALUATION METRICS

In order to assess the performance of the brain hemorrhage segmentation model, several standard evaluation metrics were used. These metrics are essential for understanding the model's ability to correctly identify hemorrhage regions and distinguish them from non-hemorrhage areas. Below is a detailed explanation of the key evaluation metrics

Dice Coefficient

The Dice coefficient is one of the most commonly used metrics for evaluating segmentation accuracy, particularly in medical image segmentation tasks. It measures the overlap between the predicted segmentation mask and the ground truth.The Dice coefficient ranges from 0 (no overlap) to 1 (perfect overlap). The formula for the Dice coefficient is:

$$\mathrm{DSC} = \frac{2|A \cap B|}{|A| + |B|} \tag{5.1}$$

where, A is the set of predicted pixels, and B is the set of ground truth pixels.

Accuracy

Accuracy is a general measure of how well the model performs in predicting both hemorrhage and non-hemorrhage areas. It is calculated as the ratio of correctly predicted pixels (true positives and true negatives) to the total number of pixels in the image. High accuracy suggests that the model is able to correctly classify both hemorrhage and non-hemorrhage regions. The formula for accuracy is:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{5.2}$$

TP: True Positives
TN: True Negatives
FP: False Positives
FN: False Negatives

Precision

Precision is a metric that focuses on the accuracy of the positive predictions made by the model. It is the ratio of true positive predictions to the total number of pixels predicted as hemorrhage. High precision indicates that when the model predicts a hemorrhage, it is highly likely to be correct. Precision is calculated as:

$$\text{Precision} = \frac{TP}{TP + FP} \tag{5.3}$$

Recall

Recall measures the model's ability to correctly identify all true hemorrhage pixels in the image. It is the ratio of true positives to the total number of actual hemorrhage pixels (true positives plus false negatives). A high recall value indicates that the model is good at identifying the majority of hemorrhage regions, minimizing the number of false negatives. The formula is:

$$\text{Recall} = \frac{TP}{TP + FN} \tag{5.4}$$

5.2 SEGMENTATION RESULTS OF 3D U-NET MODEL

Figure 5.1 illustrates the segmentation results produced by the 3D U-Net model on a brain CT scan. The results demonstrate the following:

Original CT: The input brain CT scan showing the hemorrhagic region, which needs to be segmented.
Ground Truth: The manually annotated ground truth highlighting the hemorrhagic regions in the CT scan.
Cleaned Prediction: The output from the 3D U-Net model after post-processing, accurately delineating the hemorrhagic regions.

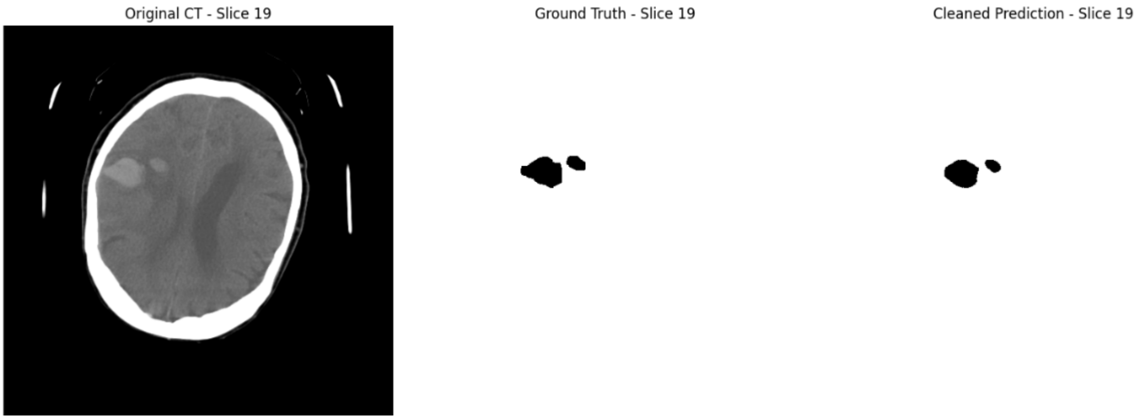

Figure 5.1: Segmentation Results

The model effectively captures the boundaries of the hemorrhagic region, aligning closely with the ground truth annotations, demonstrating its robustness and precision in segmentation tasks. This visual validation further supports the quantitative performance metrics, such as the achieved Dice Coefficient of 0.9059, signifying the model's high reliability.

5.3 MODEL PERFORMANCE ANALYSIS

The results, as summarized in Table 5.1, demonstrate that among the evaluated models, 3D U-Net outperforms both 3D ResUNet and DeepMedic in most metrics. 3D U-Net achieved the highest Dice Coefficient 0.90 and Accuracy 0.98, highlighting its superior ability to accurately segment brain hemorrhages. DeepMedic, while showing competitive Recall 0.88, had a lower

Table 5.1: Model Performance

Metric	Dice Coefficient	Accuracy	Precision	Recall
3D U-NET	0.90	0.98	0.91	0.89
3D ResUNet	0.83	0.95	0.84	0.87
DeepMedic	0.86	0.96	0.83	0.88

Precision 0.83, indicating a higher rate of false positives compared to 3D U-Net.

In contrast, 3D ResUNet exhibited the lowest Dice Coefficient 0.83 and Precision 0.84, making it the least effective among the three models.

Overall, the results suggest that 3D U-Net provides the most balanced and robust performance across all metrics, making it the optimal choice for brain hemorrhage segmentation in this study.

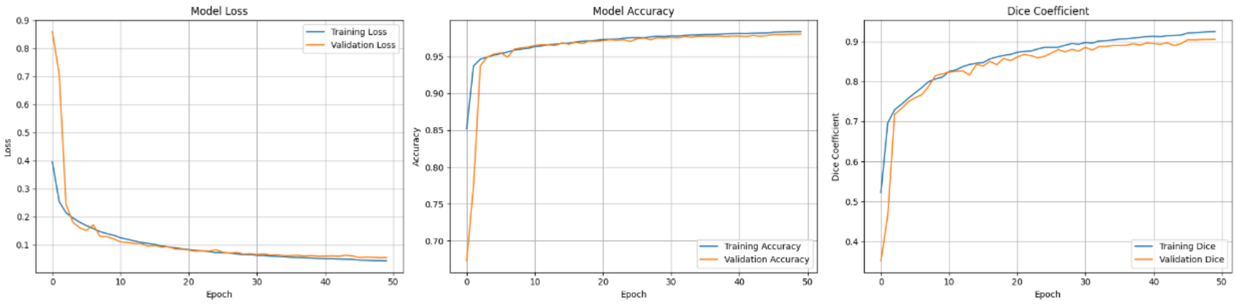

Figure 5.2: 3D U-Net Model Performance

From Figure 5.2, we observe the performance metrics of the 3D U-Net model across training and validation phases. The results are divided into three key graphs:

Model Loss: The loss decreases progressively for both training and validation datasets as the epochs increase, indicating improved model optimization.

Model Accuracy: The accuracy improves steadily for both training and validation, with validation accuracy closely following the training accuracy. This consistency shows that the model generalizes well without significant overfitting.

Dice Coefficient: The Dice coefficient, which is crucial for segmentation tasks, increases over epochs, confirming the model's ability to accurately segment hemorrhagic regions. The close overlap between training and validation Dice scores demonstrates the robustness of the model.

These plots highlight the effective training of the 3D U-Net model and its capability to generalize to unseen data while maintaining high segmentation performance.

5.4 SUMMARY

This chapter analyzed the performance of brain hemorrhage segmentation models using key metrics. 3D U-Net outperformed 3D ResUNet and DeepMedic, achieving the highest Dice Coefficient 0.9059 and Accuracy 0.98, demonstrating its effectiveness in segmentation tasks. The model showed consistent training and validation performance, with improved loss, accuracy, and Dice Coefficient over epochs. These results highlight 3D U-Net's robustness and clinical potential for brain hemorrhage segmentation.

CHAPTER 6

CONCLUSION AND FUTURE WORK

6.1 CONCLUSION

The project aimed to develop an efficient method for brain hemorrhage segmentation using 3D deep learning models and evaluated several state-of-the-art models, including 3D U-Net, 3D ResUNet, and DeepMedic. The 3D U-Net model emerged as the best-performing model, outperforming both 3D ResUNet and DeepMedic in terms of segmentation accuracy. This indicates the superiority of 3D U-Net in capturing complex patterns and structures within 3D brain scans, making it an effective tool for automated hemorrhage detection.

The results demonstrate significant potential for the 3D U-Net model in clinical applications, such as aiding radiologists in accurately identifying and delineating hemorrhagic lesions in brain CT scans. By automating the segmentation process, the model could reduce human error, speed up diagnosis, and help in better treatment planning for patients suffering from brain hemorrhages. The model achieves a Dice Coefficient of 0.9059, highlighting its high precision and reliability in segmentation tasks. Additionally, its ability to work with 3D scans ensures the handling of complex volumetric data, which is essential for detailed and precise analysis of hemorrhagic regions.

6.2 FUTURE WORK

Future work will focus on extending the model to multi-class classification, enabling the identification and classification of different types of brain hemorrhages, such as intraparenchymal, subdural, and epidural hemorrhages. Additionally, the model's performance can be improved by experimenting with advanced architectures, data augmentation techniques, and evaluating the model on larger and more diverse datasets to enhance its generalization across various clinical scenarios. Integration of the model into real-time clinical decision support systems and exploring various deep learning models for further development. This will help refine the model, making it more accurate and applicable in clinical settings.

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