# ISCHEMIC STROKE LESION SEGMENTATION FROM DIFFUSION-WEIGHTED MRI USING DEEP ENSEMBLE LEARNING

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M.Sc. Engineering Thesis

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## DECLARATION

I hereby certify that the research detailed in the aforementioned thesis is entirely original and has not been previously submitted for credit toward any degree or for any other purpose. Additionally, I affirm that all information presented in this thesis was created by me, and any sources or assistance I received have been duly acknowledged and credited in the reference section.

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ABSTRACT

# ISCHEMIC STROKE LESION SEGMENTATION FROM DIFFUSION-WEIGHTED MRI USING DEEP ENSEMBLE LEARNING

Strokes are a leading cause of premature mortality in developed and developing countries, and early treatment assistance can significantly prolong a patient's life. How quickly the lesion is determined from MRI images is the primary rehabilitative step in stroke therapy. However, manual lesion identification takes time and is susceptible to both intra- and inter-observer inconsistencies. Since manual lesion detection is highly time-consuming, it can negatively impact patient outcomes and overall experience. To aid in diagnosis, treatment planning, and analysis, medical image segmentation separates a medical image into individual parts or segments, each corresponding to a particular anatomical structure or tissue, such as organs, lesions, or other areas of interest. In light of this, computerized estimation of the outcome of the ischemic stroke lesion can assist physicians in better evaluating the stroke and providing information on tissue outcomes. So, this will be an essential tool for assessing the extent of brain cell damage. Convolutional neural networks (CNN) have been extensively utilized in the categorization of abnormalities from brain images in recent years. So, this can be achieved by accurately classifying the characteristics of ischemic stroke lesions employing a convolutional neural network with convolutional layers. Consequently, to separate the Ischemia in the current study, a deep-learning network is employed in this thesis. The primary discovery of this work is the extraction of ischemic lesion characteristics by utilizing the InceptionV3 network and the preservation of Z-axis information by employing a conventional 3D U-NET architecture. The proposed model was trained and tested using the ISLES-2017 dataset, and the experimental results obtained an overall segmentation Dice Coefficient of 0.43. The results of this investigation show that the proposed technique is superior to earlier studies.

## সারসংক্ষেপ

# ISCHEMIC STROKE LESION SEGMENTATION FROM DIFFUSION-WEIGHTED MRI USING DEEP ENSEMBLE LEARNING

স্ট্রোক উন্নত এবং উন্নয়নশীল দেশগুলিতে অকাল মৃত্যুর একটি প্রধান কারণ, এবং প্রাথমিক চিকিৎসা সহায়তা রোগীর জীবনকে উল্লেখযোগ্যভাবে দীর্ঘায়িত করতে পারে। স্ট্রোকের চিকিৎসার প্রাথমিক পদক্ষেপ হচ্ছে কত দ্রুত এমআরআই (MRI) চিত্র থেকে ক্ষতটি সনাক্ত করা যায়। তবে, হস্তকৃতভাবে ক্ষত শনাক্ত করা অত্যন্ত সময় সাপেক্ষ এবং এটি পর্যবেক্ষকদের মধ্যে অসঙ্গতির সৃষ্টি করতে পারে পারে ফলে, রোগীর ফলাফল এবং সামগ্রিক অভিজ্ঞতায় নেতিবাচক প্রভাব ফেলতে পারে। রোগ নির্ণয়, চিকিৎসা পরিকল্পনা ও বিশ্লেষণে সহায়তার জন্য মেডিকেল ইমেজ সেগমেন্টেশন একটি বিশেষ প্রক্রিয়া, যার মাধ্যমে মেডিকেল ইমেজকে বিভিন্ন অংশ বা খণ্ডে বিভক্ত করা হয়, যেখানে প্রতিটি অংশ একটি নির্দিষ্ট শারীরবৃত্তীয় গঠন বা টিস্যুর সঙ্গে সম্পর্কিত অংশগুলো, যেমন অঙ্গ, ক্ষত বা অন্যান্য গুরুত্বপূর্ণ এলাকা সম্পর্কে ধারণা পাওয়া যায়। এই প্রেক্ষাপটে, ইস্কেমিক স্ট্রোকের ক্ষতের ফলাফলের কম্পিউটারভিত্তিক অনুমান দ্বারা ডাক্তারগন টিস্যুর বর্তমান অবস্থান সম্পর্কে ধারণা এবং স্ট্রোকটিকে আরও ভালভাবে মূল্যায়ন করতে সক্ষমতা অর্জন করতে পারে। সুতরাং, মস্তিষ্কের কোষের ক্ষতর পরিমাণ মূল্যায়নের জন্য এটি একটি গুরুত্বপূর্ণ সরঞ্জাম হয়ে উঠতে পারে। সাম্প্রতিক বছরগুলিতে মস্তিষ্কের চিত্রগুলি থেকে অস্বাভাবিকতা শ্রেণীকরণে কনভোল্যুশনাল নিউরাল নেটওয়ার্ক (CNN) ব্যাপকভাবে ব্যবহার করা হয়েছে। সুতরাং, কনভলিউশনাল নিউরাল নেটওয়ার্ক এবং কনভলিউশনাল স্তর ব্যবহার করে ইস্কেমিক স্ট্রোকের মৃত কোষ গুলোর বৈশিষ্ট্য সঠিকভাবে শ্রেণীবদ্ধ করা যেতে পারে। ফলস্বরূপ, বর্তমান গবেষণায় ইস্কেমিক স্ট্রোকের মৃত কোষ গুলোকে আলাদা করার জন্য, একটি গভীর-শিক্ষার (Deep-learning) নেটওয়ার্ক নিযুক্ত করা হয়েছে। এই গবেষণায়র প্রধান অবদান হল InceptonV3 নেটওয়ার্ক ব্যবহার করে ইস্কেমিক স্ট্রোকের মৃত কোষ গুলোকে নিষ্কাশন এবং 3D U-NET আর্কিটেকচার (Architecture) ব্যবহার করে Z অক্ষের তথ্য সংরক্ষণ করার মাধ্যমে শুধুমাত্র ইস্কেমিক স্ট্রোকের মৃত কোষগুলোর বৈশিষ্ট্যগুলো নিয়ে এম আর আই (MRI) টিকে পুনর্গঠন করা হয়েছে। প্রস্তাবিত মডেলটিকে ISLES-২০১৭ ডাটাসেট ব্যবহার করে প্রশিক্ষণ এবং পরীক্ষা করা হয়েছে এবং পরীক্ষালব্ধ ফলাফল হিসেবে ডাইস সহগ (Dice Coefficient) ০.৪৩ অর্জন করা সম্ভব হয়েছে। এই গবেষণার ফলাফলগুলি পূর্ববর্তী পূর্ববর্তী গবেষণাগুলোকে ছাড়িয়ে গেছে তা প্রদর্শন করে।

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# LIST OF ABBREVIATION

| | |
|---|---|
| **AIS** | : Arterial Ischemic Stroke |
| **SLR** | : Systematic literature review |
| **CT** | : Computed tomography |
| **MRI** | : Magnetic resonance imaging |
| **DWI** | : Diffusion-weighted imaging |
| **CNNs** | : Convolutional Neural Networks |
| **SVM** | : Support Vector Machines |
| **CDSS** | : Clinical Decision Support Systems |
| **CAD** | : Computer-aided diagnosis |
| **RNNs** | : Recurrent Neural Networks |
| **BET** | : Brain Extraction Tool |
| **NIFTI** | : Neuroimaging Informatics Technology Initiative |
| **DICOM** | : Digital Imaging and Communications in Medicine |
| **FCN** | : Fully Convolutional Network |
| **ISLES** | : Ischemic Stroke Lesion Segmentation |
| **ASPP** | : Atrous spatial pyramid pooling |
| **DL** | : Deep-learning |
| **ML** | : Machine Learning |
| **AI** | : Artificial Intelligence |
| **WHO** | : World Health Organization |

# CHAPTER 1

# INTRODUCTION

This chapter comprises of the thesis background that includes an overview of the key research topic. Here, the motivation and problem statements of the thesis have been highlighted. Following that, the thesis objectives are stated point by point. Next, the overall methodological framework of the thesis has been presented. And finally, the organization of the remaining chapters of the thesis is described.

## 1.1 Background

In recent times, stroke has emerged as a significant health concern, representing the most widespread and potentially life-threatening cerebrovascular condition. Despite improvements in medical care, stroke remains the third most common cause of death and disability and the second largest cause of mortality. It is startling to learn from statistics that one in every six people may suffer a stroke at some time. Stroke has a startling worldwide effect, causing about 13.7 million cases annually and the terrible death of 5.8 million people. Reduced or interrupted blood flow to a particular region of the brain causes a stroke, which ultimately results in the death of brain cells owing to a shortage of oxygen and nutrients supplied by the blood. Ischemic stroke and hemorrhagic stroke are the two primary forms of strokes. A hemorrhagic stroke develops when blood vessels burst, producing bleeding into the brain, whereas an ischemic stroke arises when blood arteries in the brain become clogged or obstructed. Ischaemic strokes account for around 70% of all stroke cases, making them the more common. Subarachnoid hemorrhage and intracerebral hemorrhage make up the majority of the remaining strokes. Ischemic strokes are thought to account for an even larger percentage of cases, anywhere between 85% to 87%. Ischemic strokes happen when a thrombus or an embolus blocks a blood artery. The categorization of an ischemic stroke has changed from being mostly clinical to being tissue-based as a result of advancements in brain imaging.

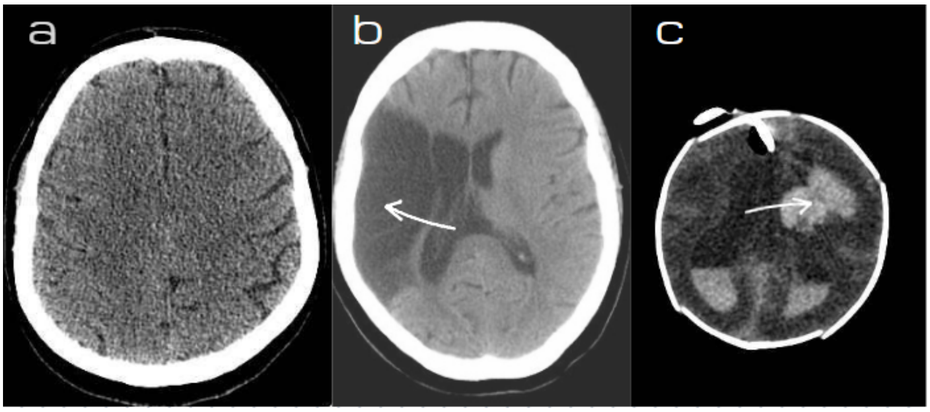


**Fig. 1.1.** a) Healthy brain b) Ischemic stroke c) Hemorrhagic stroke.

Additionally, thrombotic strokes and embolic strokes are two categories of Ischaemic strokes. A thrombotic stroke, on the other hand, happens when a clot forms in a blood artery in your brain. When a blood clot travels from another region of the body to the brain, an embolic ischemic stroke develops. The speed at which a patient may be transported to a hospital affects the course of therapy for an Ischaemic stroke. Additionally, the patient's medical background has an impact on them. Acute Ischaemic stroke occurs during the first 24 hours, subacute stroke occurs over the next 2 weeks, and chronic stroke occurs after 2 weeks or beyond. Hence, this thesis is mainly focusing on Ischaemic stroke.

## 1.2 Motivation

In recent research, it has been observed that approximately 700,000 people in the United States suffer from a stroke every year. Furthermore, around 2 million stroke survivors are living in the United States, many of whom face long-term disabilities and struggle to work or rebuild personal connections. In China, stroke claims the lives of 1.5 million people annually, making it the third leading cause of death in affluent countries, ranking just behind heart disease and cancer. The cost of healthcare in the United States is estimated to exceed 62 billion dollars each year. When an infection is present before an ischemic stroke, the severity and clinical prognosis may be worse. Patients with recent infections have been reported to have strokes that are more severe in terms of neurological damage at presentation, albeit not all study findings support this claim. Therefore, The traditional clinical approach of Ischaemic stroke detection requires sophisticated procedures with the supervision of expert clinicians (radiologists) which may become difficult to manage. For the factors of disability and mortality in an Ischemic stroke patient, early treatment is necessary. Without an essential medical tool, it is not possible to initiate early treatment. If an Ischemic patient takes two to three weeks to begin treatment, the rates of disability and mortality will increase.

### 1.3 Problem Statement

In modern medical technology, there is no such medical equipment able to recognize the severity level of an Ischemic stroke. Due to the complex structure of the brain Ischemic lesion, detecting or segmenting the Ischemic stroke area is challenging. As a result, scientists all around the world are currently striving to create an efficient method for detecting ischemic strokes that makes use of a range of modern computational approaches. However, a limited number of studies have been conducted for efficient prediction and diagnosis of Ischemic stroke using advanced computational techniques. Also, few studies have been performed to explore the minimal and most significant features of Ischemic stroke detection. Most of the existing ML-based studies emphasized predicting Ischemic stroke using either symptom data or MRI, CT, and CTA images, exploring the optimum set of features, and finding out the best-performing classifier by implementing traditional and ensemble (bagging, boosting) ML models. Therefore, by utilizing imaging data such as MRI, CT, and CTA, an expanded or integrated machine learning strategy may improve prediction performance and lower computing complexity for predicting Ischemic stroke. To improve the present ML-based models by adding various innovative ML approaches like deep learning, transfer learning, etc., more research is necessary to examine extended ML classifiers. The study involved discovering and shortlisting imaging methods and ensemble deep-learning techniques for segmenting the ischemic stroke area. The performances of these methods were analyzed to assess their effectiveness. After that, an ensemble machine learning segmenter has been designed, trained, and evaluated in the second phase utilizing the dataset of the patients. Additionally, at this stage, the suggested technique's effectiveness has been compared to other deep learning-based models for segmenting ischemic stroke using image data (satisfying research target 3). To achieve study goal 3, an ensemble deep learning segmenter that combines conventional a deep learning-based neural network has been designed, trained, and evaluated using MRI images. Additionally, a performance comparison between the proposed method and other methods already in use for segmenting brain MRI image data has been done at this point.

The problem statement is summarized with a few important aspects.

- Though in medical image segmentation, 3D-UNT architecture shows comparatively better performance, very few studies have found where 3D-Unet is used; moreover, the integration of inception and 3D-UNET is rarely unidentified in the literature review section.
- Explore methods for effectively extracting both global and local features to improve model performance and incorporate Z-axis features to capture and utilize 3D spatial information for more comprehensive analysis.
- Develop an advanced AI tool for the segmentation of ischemic stroke areas, enhancing overall segmentation accuracy.

## 1.4 Thesis Objectives

- To identify various deep learning models used in brain stroke segmentation from DW-MRI, and selection of capable of suitable method.
- To integrate Inception family with 3D-UNET and testing the usability of the models.
- To implement and result analysis of the proposed method, using ISLES 2017 dataset.

## 1.5 Methodological Overview

The study work's technique has been roughly separated into three parts to achieve the thesis' goals. To get comprehensive information in this field, a systematic literature review

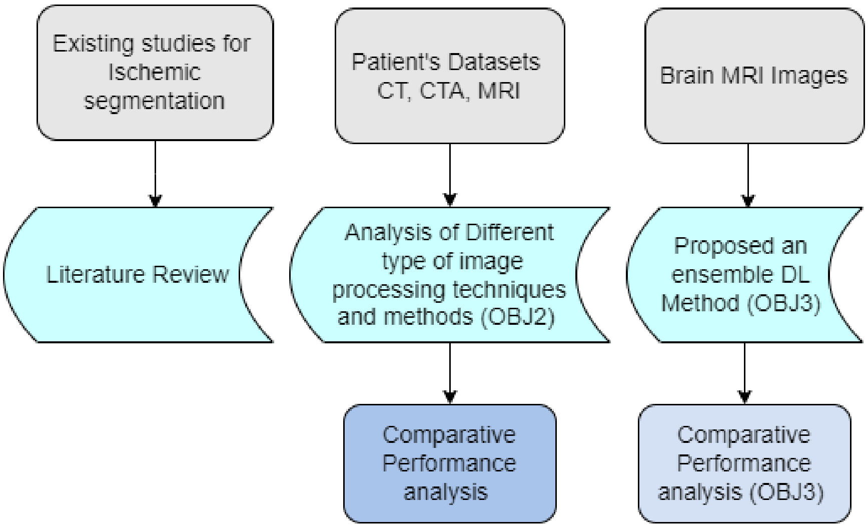


**Fig. 1.2.** Framework of methodological overview

has been created at the early stage after a thorough analysis of the relevant research that has already been conducted on the topic of Ischemic stroke prediction utilizing various machine learning approaches and deep learning to achieve study aims 1. The study involved discovering and shortlisting imaging methods and ensemble deep-learning techniques for segmenting the ischemic stroke area. The performances of these methods were analyzed to assess their effectiveness. After that, an ensemble machine learning segmenter has been designed, trained, and evaluated in the second phase utilizing the dataset of the patients. Additionally, at this stage, the suggested technique's effectiveness has been compared to other deep learning-based models for segmenting ischemic stroke using image data (satisfying research target 3). To achieve study goal 3, an ensemble deep learning segmenter that combines conventional a deep learning-based neural network has been designed, trained, and evaluated using MRI images. Additionally, a performance comparison between the proposed method and other methods already in use for segmenting brain MRI image data has been done at this point. Figure 1.2 illustrates the methodological overview's conceptual framework.

## 1.6 Contribution of the Thesis

The most recent deep-learning methods have been used in this thesis to segment ischemic stroke lesions. This experiment was performed to support assertions. In this work, the proposed deep learning (DL) model was trained using an MRI dataset.

- The model demonstrated superior performance over other models and fulfilled the main goal of this thesis with a Dice Similarity Coefficient (DSC) of 43% after training, validating, and testing.
- Another contribution of this thesis is extracting data of dead cells from MRI images using the Inception module while considering the time complexity and good performance.
- The proportion of true negatives is low despite the limited training dataset; the qualitative analysis part of this thesis provides a full explanation of this.
- Along with this work, this thesis includes extensive research on datasets, models, and other aspects of this domain.

Overall, the study's findings can significantly aid doctors in their difficult patient evaluation process by demystifying the intricate ischemic stroke diagnosis process. This computational method can be used in remote healthcare facilities to automatically identify ischemic strokes in situations when resources and skilled medical personnel are limited.

## 1.7 Organization of the Chapters

The rest of the thesis has been structured in the following way:

Chapter 2 describes the necessary theoretical background of the study, which includes the primary discussion about the Ischemic stroke condition in the human brain, how automated detection of Ischemic stroke can aid in this domain, the existing works on Ischemia detection using various computer-aided technologies and brain images, as well as the research gaps in these areas. And also includes the systematic literature review (SLR) of the related works in this domain; which demonstrates the methodology utilized for conducting the SLR, the data extraction and analysis process from the relevant studies, and finally the summarizing of the review findings with potential research opportunities in this domain.

Chapter 3 depicts and demonstrates the methodology and discussion of the proposed Ensemble DL method for Ischemic Stroke segmentation from imaging techniques. And also demonstrates the dataset, environmental setup, and Implementation.

Chapter 4 demonstrates the comparative performance analysis of the proposed technique with other existing techniques.

Finally, Chapter 5 of the thesis presents the discussion and conclusion of the research work with the thesis outcome, implications, limitations, and future plan of this study.

# CHAPTER 2

## THEORETICAL BACKGROUND AND RELATED WORKS

This chapter briefly discusses the key concepts to provide basic theoretical knowledge regarding the background of this thesis. At first, a preliminary discussion on Ischemic Stroke is presented. Then Imaging Techniques for Brain Ischemic Stroke and some details about the detection of advanced technologies. And the overview of systematic literature review (SLR) of the related works in this domain.

### 2.1 Brain Ischemic Stroke

Ischemic stroke is a heterogeneous disease that occurs due to a variety of underlying pathological processes. The blockage of an artery is the main cause of Ischemic brain stroke. It occurs when blood vessels in the brain become narrowed or blocked, resulting in a significant decrease in blood flow.

#### 2.1.1 Anatomical Background

**Endothelial cell Dysfunction:** When the smooth inner lining of the artery, known as the tunica intima, becomes irritated or inflamed, one mechanism of concern is endothelial cell failure. Toxins from tobacco are a frequent irritation because they harm the endothelium and circulate in the blood. This injury creates an environment that is conducive to the development of atherosclerosis, which is the blockage of arterial blood flow caused by the buildup of proteins, lipids, cholesterol, immune cells, and calcium in the form of a plaque. Plaques usually accumulate over years and partially obstruct the arteries. Some blood still gets through despite the decreased blood supply to the brain tissue as a result of this. A abrupt, total, or almost total blockage of an artery results in a stroke.

**Embolism:** A blood clot that has moved from its initial site and lodged itself in a downstream narrower artery, arteriole, or capillary is often the cause of an embolic stroke. Although the heart can potentially become the site of these clots, atherosclerosis is usually the initial cause.

**Lacunar Stroke:** A lacunar stroke is a particular kind of ischemic stroke that usually affects the deep branches of the middle cerebral artery that supply the brain's neurons. Hyaline arteriolosclerosis, a disorder in which protein deposits thicken the walls of arterioles, frequently causes lacunosar strokes. This thickening, which is frequently brought on by diabetes or hypertension, shrinks the artery's lumen. Because healthy tissues use oxygen and nutrients from the blood, they deplete the resources available to tissues farther down the pathway, causing the tissues downstream to be most affected. These ”furthest downstream” brain regions are located where two distinct blood streams converge. These regions are especially prone to injury if there is a decrease in blood flow throughout the body.

The brain tissue that is most likely to perish from a lack of blood flow is known as the ischemic core, and the ischemic penumbra surrounds it, regardless of the underlying etiology of an ischemic stroke. Cells quickly run out of energy when they aren't getting enough glucose and oxygen, which causes sodium and calcium levels to rise significantly in a matter of minutes. Water enters the cell as a result of high salt levels, causing swelling known as cytotoxic edema. Elevated calcium concentrations lead to the build-up of reactive oxygen species, which then interact with the lipids found in the membranes of lysosomes and mitochondria. Degradative enzymes and substances that induce death can escape the cells as a result of this damage. After a long discussion, acute ischemic stroke (AIS) is described as a loss of neurologic function caused by a sudden decrease of blood supply to a part of the brain. Thrombosis or embolism that obstructs a cerebral vessel supplying a specific area of the brain causes it.

## 2.2 Imaging Techniques of Brain Ischemic Stroke

The term "computed tomography" or CT scan refers to a computerized X-ray imaging procedure in which a narrow X-ray beam is directed at a patient and rotates rapidly around the body, which is then processed by a computer to generate an image or "slice" of the body. After collecting multiple consecutive slices on the machine's computer, they can be digitally stacked together to form a 3D image of the patient, which simplifies the identification and location of underlying structures as well as potential tumors or anomalies.

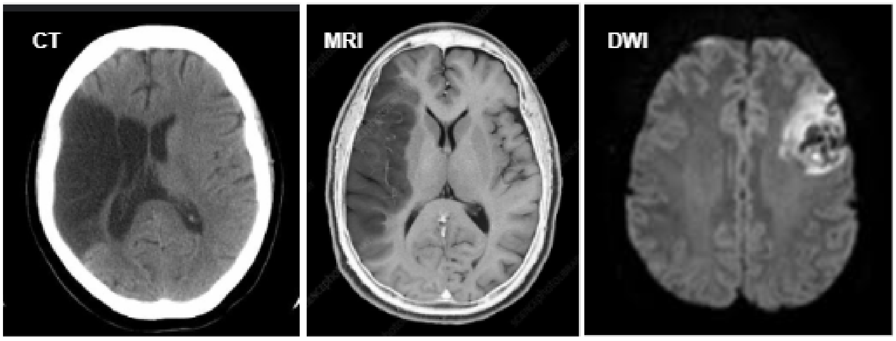


**Fig. 2.1.** Different Imaging Techniques of Stroke

A non-invasive magnetic field and computer-generated radio waves are used in MRI, a medical imaging procedure that produces precise three-dimensional anatomical pictures of your body's organs and tissues. The MRI machine employs magnetic and radiofrequency radiation to take a picture of the patient's body. A signal is transmitted to the computer by the energy released by atoms in a magnetic field. The computer then applies mathematical procedures to transform the signal into a picture. A kind of magnetic resonance imaging called diffusion-weighted imaging (DWI) quantifies the random Brownian motion of water molecules inside a tissue voxel. In general, tissues that are heavily cellular or have cellular swelling have lower diffusion coefficients. Diffusion is very beneficial in identifying tumors and detecting cerebral ischemia. In CT images, a hemorrhage appears as a bright region well contrasted against its surroundings and an ischemic stroke appears as a dark region with a contrast, relative to its surroundings. However, the main indicator of an ischemic stroke, a hypodense lesion, is not visible in the initial hours following the stroke, although improvements in MRI technology have made it possible to see minor lesions in brain scans.

## 2.3 Ischemic Stroke Detection

Automatic detection of ischemic stroke is an important area of research and development in medical imaging and healthcare. Ischemic stroke occurs when there is a blockage or clot in a blood vessel, leading to reduced blood flow to the brain. Early and accurate detection is crucial for prompt intervention and treatment, which can significantly improve patient outcomes. Numerous investigations have been carried out to explore computer-aided Ischemic Stroke detection methods, which present significant benefits such as quick diagnosis in the least amount of time with the least amount of human error and effort. Machine learning techniques are emerging as one of the most popular, effective, and promising predictive strategies due to the massive growth of healthcare data and the use of information technology. These techniques can analyze and retrieve important information from vast amounts of heterogeneous clinical data in order to intelligently detect diseases. A number of imaging modalities are essential to this procedure, such as magnetic resonance imaging (MRI) and computed tomography (CT).

Machine learning and deep learning techniques are increasingly integrated into the detection process. Convolutional Neural Networks (CNNs) analyze complex patterns from imaging data, while traditional machine learning methods like Support Vector Machines (SVM) extract features for classifying images as indicative or non-indicative of ischemic stroke. These algorithms leverage large datasets to enhance accuracy. Moreover, Clinical Decision Support Systems (CDSS) integrate imaging modalities and clinical data into comprehensive tools that assist healthcare professionals in making informed decisions about ischemic stroke diagnosis and treatment. These systems enhance the overall efficiency and accuracy of the diagnostic process. An ischemic stroke appears as a black region with a contrast, compared to its surroundings, while a hemorrhage appears as a bright region well contrasted against its surroundings in CT images. The key indicator of an ischemic stroke, a hypodense lesion, is not visible in the first few hours following the commencement of the stroke, although improvements in MRI technology have increased the possibility of seeing minor lesions in brain pictures (Jeena and Kumar, 2013). As a result, it is now possible to identify cerebral microbleeds, which are minor brain hemorrhages linked to an increased risk of ischemic stroke and intracerebral bleeding. Computed tomography (CT) imaging and magnetic resonance imaging (MRI), each one with its particular particularities for the detection of Brain stroke. MRI is more precise but is only available in large hospitals, while CT is more common but less precise. Figure 2.2 illustrates the brain stroke detection system of a CAD (computer-aided diagnosis).

In summary, the automatic detection of ischemic stroke relies on a combination of advanced imaging modalities and sophisticated data analysis techniques. Ongoing research continues to refine and improve these methods, contributing to enhanced diagnostic capabilities and better patient outcomes in the realm of ischemic stroke management.

## 2.4 Machine Learning and Deep Learning Techniques for the Detection of Ischemic Stroke

The application of machine learning techniques has become instrumental in the realm of medical diagnostics, particularly in the detection of ischemic stroke. Leveraging advanced algorithms and pattern recognition from medical imaging data, machine learning contributes significantly to the accurate and timely identification of stroke-related abnormalities. Several key techniques are employed in this context. Convolutional Neural Networks (CNNs)

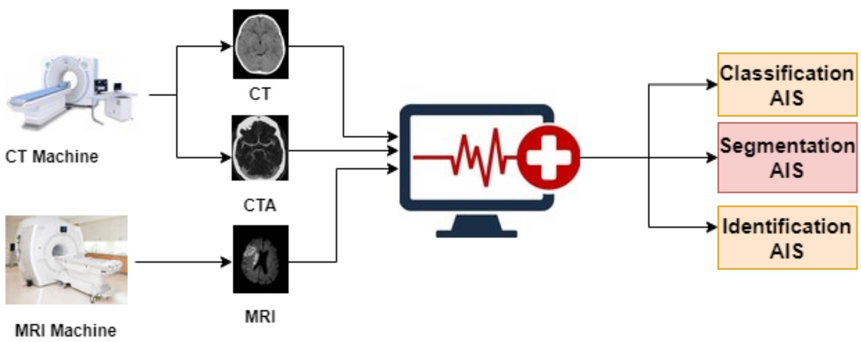


**Fig. 2.2.** CAD for Brain stroke detection system

stand out as a powerful tool in image-based tasks. When applied to medical imaging, CNNs automatically learn hierarchical features from brain scans, enabling them to detect subtle patterns associated with ischemic stroke. These networks excel in tasks involving complex image analysis, making them well-suited for analyzing computed tomography (CT) scans, magnetic resonance imaging (MRI), or angiography data to pinpoint regions indicating reduced blood flow or other anomalies indicative of ischemic stroke.

### 2.4.1 Machine Learning Techniques

Support Vector Machines (SVM) offer a robust approach to binary classification tasks, such as distinguishing between healthy and ischemic stroke-affected brain images. SVMs are effective in high-dimensional spaces, allowing them to discern non-linear relationships in the data. They are commonly used to extract features from medical images and classify them based on the presence or absence of ischemic stroke. Random Forests and Decision Trees provide another avenue for image-based classification. These methods are adept at handling complex decision boundaries and can shed light on the importance of different features in the data. In the context of ischemic stroke detection, they play a role in identifying key image features that contribute to the classification. Ensemble methods, including bagging and boosting, are employed to enhance overall model performance and robustness. By combining multiple models, these methods mitigate overfitting issues and improve generalization, contributing to a more accurate and reliable system for ischemic stroke detection.

### 2.4.2 Deep Learning Techniques

Recurrent Neural Networks (RNNs) prove valuable when dealing with sequential data, such as time-series imaging. By capturing temporal dependencies in medical imaging sequences, RNNs offer insights into dynamic changes over time, aiding in the analysis of sequential MRI data to detect patterns associated with ischemic stroke progression. Using multi-modality MRI sequences, the Res-CNN network is employed to segment the acute ischemic stroke lesions. When compared to the six traditional CNN approaches, it performs better, Res-architecture CNN's is primarily U-shaped. DenseNets significantly surpassed ResNets when they were originally introduced for the categorization of 2D natural photographs due to their novel dense connection model. These qualities are needed, especially in healthcare applications where training datasets are frequently smaller and data dimensionality might be larger.

In summary, the deployment of machine learning techniques in ischemic stroke detection represents a transformative approach in modern healthcare. These techniques, whether through advanced neural networks, classical classifiers, or ensemble methods, empower clinicians with precise and efficient tools for early diagnosis, ultimately improving patient outcomes in the face of ischemic stroke.

## 2.5 Methodology for Literature Review

Literature reviews are often the first step in any research project that offers credible findings from pertinent studies on the area of interest as well as public information. Systematic Literature Reviews (SLRs) provide a more thorough, structured synopsis that adheres to established protocols and, in an impartial manner, identifies, evaluates, and highlights the research gaps of the published studies that address specific study objectives and research issues. From a methodological standpoint, this study's SLR was carried out in three stages using the strategies recommended by Tandon et al. (2020).

### 2.5.1 Phase 1: Planning

The planning phase of the study entails determining the research objectives and research questions, developing the protocol for conducting the SLR, and preparing the requirements analysis for the review before it is carried out.

#### 2.5.1.1 Requirement Analysis:

The necessity of doing this SLR was examined during the requirement analysis phase, and as a result, the relevant background information—such as clinical viewpoints on stroke and the ways in which computer-assisted methods may aid in the diagnosis of ischemic strokes—was acquired. As of now, a large number of studies have been conducted showing how well stroke may be identified early on utilizing a variety of machine learning-based methods that work with patient information. Nevertheless, very few studies have been conducted where the results have been examined to explore the limits and future directions in this field of study, or where an overview of all these studies has been given. The requirement analysis process therefore clearly illustrates the necessity of SLR in this domain.

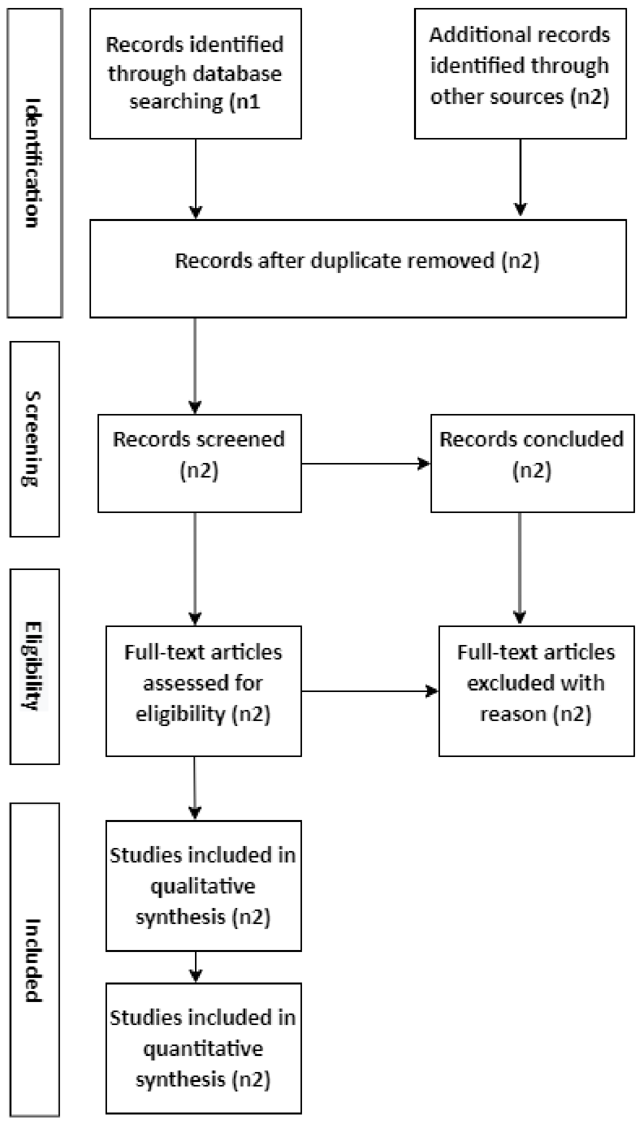


**Fig. 2.3.** PRISMA diagram for the representation of the searching method

#### 2.5.1.2 Research Objectives Identification:

The main goals of the study are to determine the value and efficacy of computer-assisted methods for ischemic stroke detection and to methodically synthesize the results, drawbacks, and potential directions for future research from the current body of work. In order to support the attainment of the study's main objective, the following auxiliary goals have been defined at this planning stage:

- RO1: to examine the objectives, publications, and research goals of the current field;
- RO2: to look at the kinds of data used in relation to the research's scope for the detection of Ischemic Stroke;
- RO3: to investigate several forms of computer-assisted methods and assessment approaches that have been applied to independent detection of ischemic strokes;
- RO4: to look at the obstacles and research findings around the detection of ischemic stroke;
- RO5: Lastly, to outline some directions for further study in the field of autonomous Ischemic Stroke detection.

### 2.5.2 Phase 2: Execution

The review has been carried out in the execution phase of the SLR, which entails finding, sorting, and choosing the research materials. The necessary data are then taken out, evaluated, and combined to investigate the review results. The execution phase's operations took place between April 2022 and January 2023.

#### 2.5.2.1 Searching, screening and finalizing review materials

In this study, a systematic guideline called "Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA)", Selçuk (2019) was used to identify the papers for systematic literature reviews. Figure 2.3 displays the PRISMA flow diagram used to choose the review materials. There are four stages to the process: inclusion, eligibility, screening, and identification.

By following the SLR authors of this thesis find the related articles, and Searching, screening, and finalizing review materials is done by using PRISMA and concept map.

| SL No. | Keywords |
|---|---|
| 1 | “Ischemic Stroke” |
| 2 | “Ischemic Stroke detection, diagnosis” |
| 3 | “Ischemic Stroke detection with CAD” |
| 4 | “Automated detection of Ischemic Stroke” |
| 5 | “Early screening of Ischemic Stroke with ML” |
| 6 | “Prediction of Ischemic Stroke” |
| 7 | “Injury identification in Ischemic Stroke” |

**Table 2.1:** List of keywords utilized for searching in database

The articles that have been published in peer-reviewed journals, conference proceedings, or as thesis dissertations are searched for during the identification phase using keywords in a variety of well-known databases, including Google Scholar, Science Direct, Scopus, Research Gate, and others. Table 3.2 contains a list of the keywords that were utilized throughout the identification phase. This method yielded a total of 752 research papers at first, which were subsequently reduced throughout the screening stage. 151 articles were left after duplicate entries, articles written in languages other than English, and articles without full text were removed during the screening stage. The final articles that meet the requirements for the SLR are carefully chosen during the eligibility phase, which takes into account all inclusion and exclusion criteria. As a result, 32 publications are eventually included for data synthesis and in-depth analysis of this study once all of these choosing processes are completed.

#### 2.5.2.2 Data extraction, analysis and synthesize:

As of this phase, the data extraction theme depicted in Figure 3.3 has been used to extract, evaluate, and synthesize data from the chosen research articles. Six facets of data extraction topics have been taken into account in order to satisfy the SLR’s study goals. For each subject, a set of questions is provided in order to obtain the specific kind of data required.

1. **Topological Association:** This subject looks at two questions in order to assess the fundamental relationship and applicability of the study literature:
   (a) Are the article titles closely related to one another?
   (b) Do the articles' keywords appear frequently?
2. **Research Profiling:** Using four sub-queries, this subject presents the research publication profiles of the chosen articles.
   (a) Which publishing types apply to the chosen studies?
   (b) What year was the publication of the studies?
   (c) Which nations do the writers of the articles hail from?
   (d) Was funding provided to carry out the study?
   (e) Which academic journals released these studies?
3. **Scope of Research:** This topic employs the following inquiry to concentrate on the context and scope of the research:
   (a) Which studies have been chosen, and what are their study goals?
4. **Data Profiling:** This theme makes use of three queries to look at the data used for the articles in accordance with the study objectives:
   (a) What kind of information is used to forecast ischemic stroke?
   (b) What sources of information have been used for the studies?
   (c) What is the volume of the dataset that was used?
5. **Methodology:** This topic focuses on the research approach that was used to achieve the study's goal by using two questions:
   (a) Which technologies or methods have been used in the selected publications to forecast Ischemic Stroke?

   (b) Which algorithms or feature selection/extraction methods were applied in order to put the suggested methodology into practice?

6. **Research Findings:** The primary study findings from the publications are organized using this data extraction topic by using the following queries:

   (a) Which papers' main research findings are they?

   (b) Which assessment metrics have been applied to evaluate the suggested methodology?

### 2.5.3 Phase 3: Assimilation

The last stage of the SLR is assimilation, which concludes the review by outlining the important variables, after the implementation step. The primary findings are presented in this step through a summary of the research findings from the chosen papers. The list of potential research gaps, restrictions, and difficulties resulting from these studies follows. Lastly, the prospective future research agenda for autonomous and effective stroke detection using machine learning and computer-assisted advanced approaches is examined in accordance with the analysis reports of all the findings.

## 2.6 Data Extraction and Analysis

A detailed description of data extraction and analysis using six themes has been discussed in this section which is conducted after the selection of the 32 eligible articles to perform SLR.

### 2.6.1 Topological Association

Wordclouds, a popular visualization method for rapidly displaying any text analytics, were created in this study to investigate the topological relationship in terms of the correlation and relevancy of the chosen articles. Two word clouds are generated here; the first uses all of the article titles (refer to Figure 2.5), while the second one refers to the keywords (refer to Figure 2.6); to address the two queries under the theme of topological association. The largest and


**Fig. 2.4.** Data extraction theme for systematic review

strongest words tend to be more significant and frequent than the smaller, less concentrated terms. The word cloud shows the frequency of the words in proportion to dimensionality that are included in the collection of keywords and titles of the articles under review. From


**Fig. 2.5.** Wordcloud of the Titles from selected articles

Figure 2.5, it is apparent that 'Stroke', 'Dysfunction', 'Embolism', 'Ischemic', 'Lacunar Stroke', 'Hemorrhagic', 'Endothelial', 'using' etc. are the most frequently utilized words in the titles of the articles. Also, from Figure 2.6, it is visible that the most frequent words utilized in the keywords of the articles are 'Segmentation', 'neural network', 'Intelligence', 'Artificial', 'Detection', 'transfer learning', 'feature', 'machine', 'classifier', 'Inception' etc.

### 2.6.2 Research Profiling

Five factors have been considered in the research profile of the chosen studies: financing, publisher name, researcher's country, publishing kind, and publication year. The information about the sort of research paper selected for publishing is included in the publication type. It is evident from the pie chart in Figure 2.7 that the chosen papers are either from conference proceedings or any publication. Of the 32 papers that were chosen, 14 came from journals, accounting for 44% of the publishing type, and 18 came from conference proceedings, which account for 56%. The study's selected research publications were all published between 2006 and 2023, as specified in the inclusion criteria. The publishing

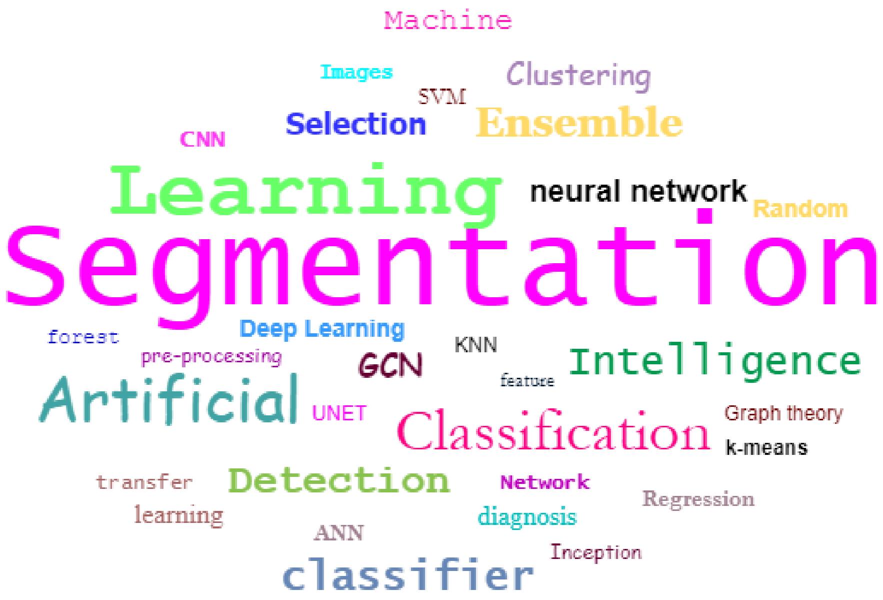


**Fig. 2.6.** Word cloud of the Keywords from selected articles

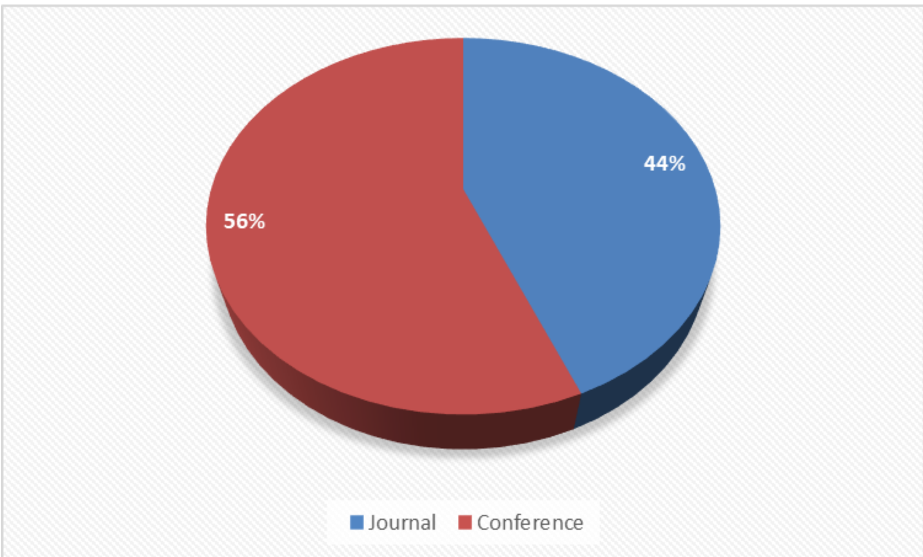


**Fig. 2.7.** Publication Type

pattern throughout this time period is depicted in Figure 2.8, which indicates that the majority of the research were carried out in 2017. It is to be mentioned that, several studies conducted in 2023 could not be included in this study as they were not available in full-text online by November 2023.

On the other hand, Figure 2.8 also shows that, before to 2011, there were fewer studies completed in this subject, and that since then, the trend of research works in this domain has

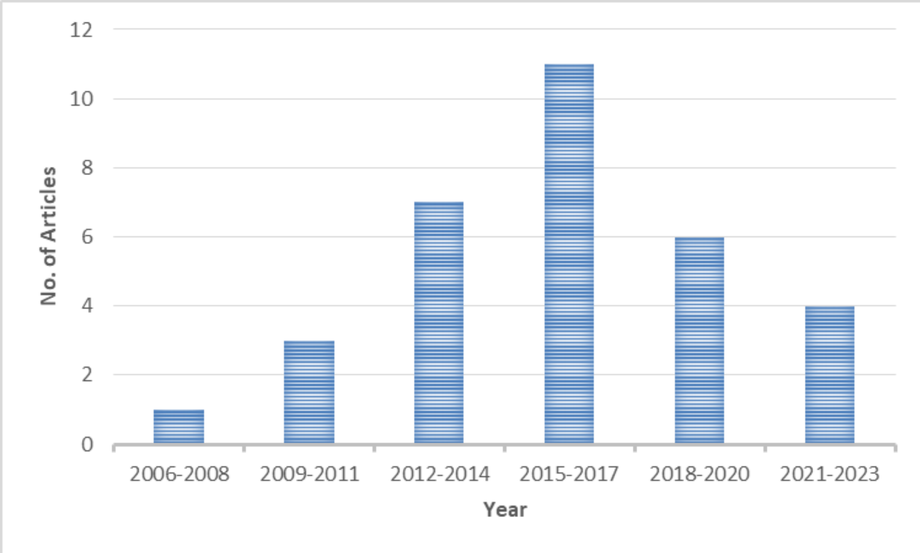


**Fig. 2.8.** Publication trend between the years 2006 to 2023

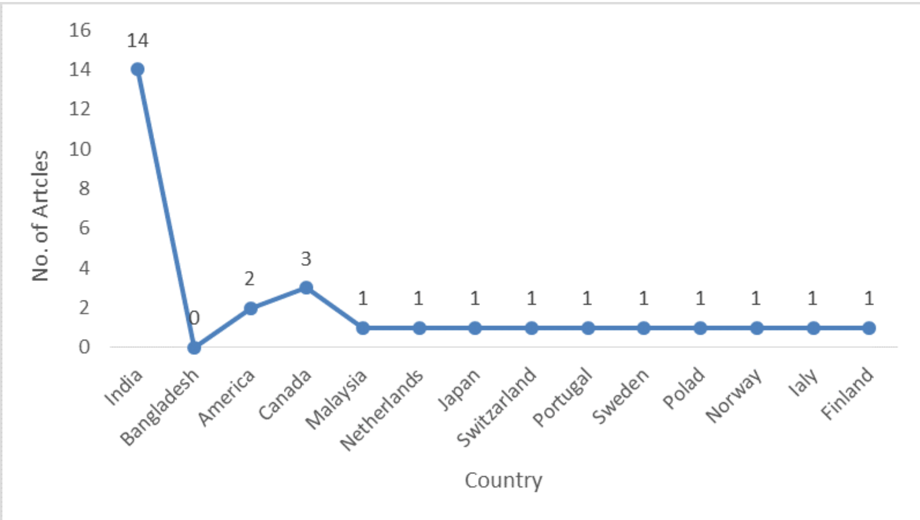


**Fig. 2.9.** Number of articles per country where the first author is affiliated

been steadily expanding. for addressing the nations from where this field's study has been carried out.

A visual representation of Figure 2.9 has been provided. The initial author of the paper is affiliated with the department of the institution indicated by the name of the nation. As can be seen from the chart, the majority of study in this field has been carried out on the Asian subcontinent, with Bangladesh coming in last with 0 studies, followed by India with 14. Other studies from Canada, Malaysia, and other countries have also been considered for assessment in this research. The next issue is to organize the papers according to their

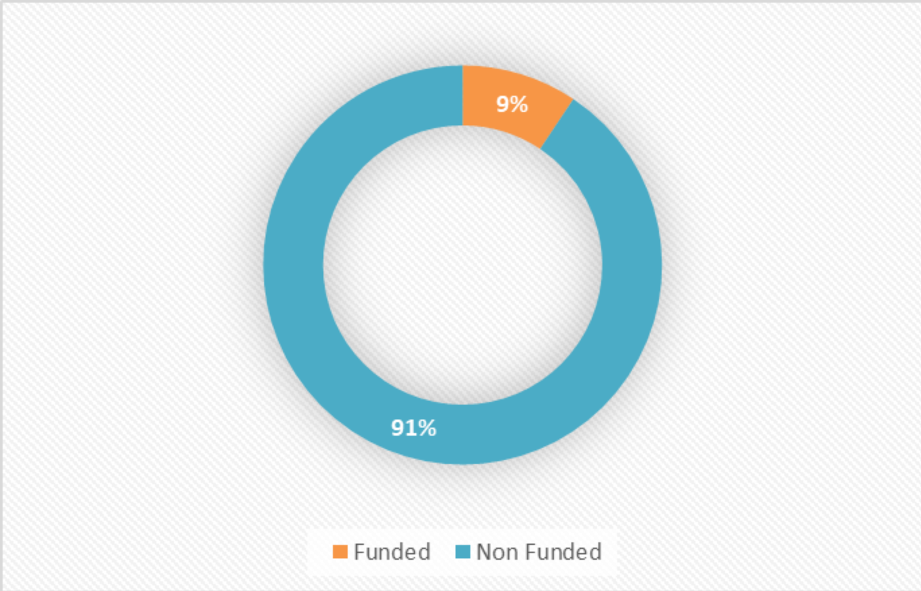


**Fig. 2.10.** Funding information

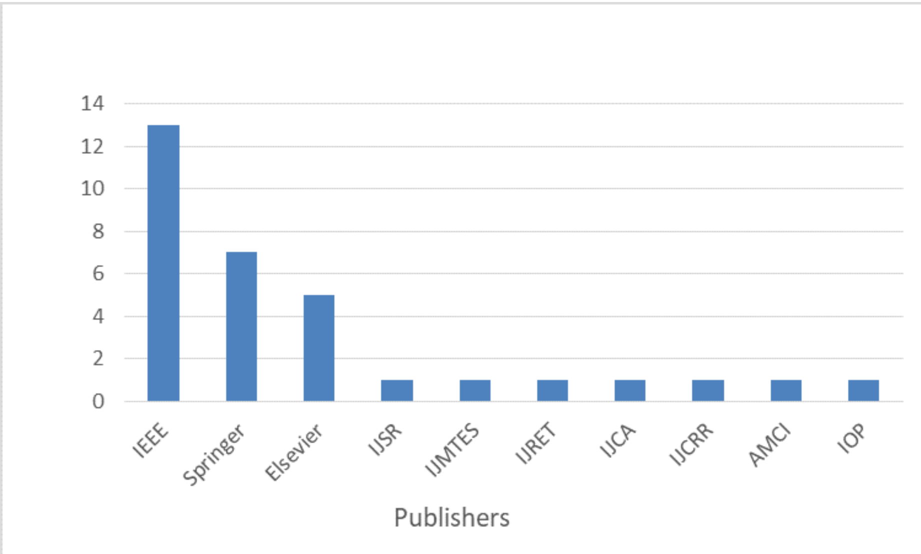


**Fig. 2.11.** Number of articles as per Publisher's name

financing alternatives within the data extraction topic based on research profiling.

As can be seen from the donut chart in Figure 2.10, the majority of the studies (91%) did not get any financial assistance to carry out their study, with just 9% (3 out of 32) receiving funding from any organization.

The publisher's names are arranged in Figure 2.11 according to the quantity of articles in order to answer the last question under this subject. According to the graphical depiction, IEEE has published the most research done to segment Ischemia using computer-assisted methodologies (13 papers), followed by Springer with 7 publications. On this study topic, papers have also been published by a number of other publications, including IOP, Elsevier, IJSR, AMCI, etc.

### 2.6.3 Scope of Research

Based on their main research goals, the 32 studies that made up the total have been categorized into six groups in order to examine the extent of the chosen research works. The first set of experiments used feature selection approaches to identify the most important information from patient data. They then used machine learning classification models to identify ischemia based on the smaller collection of features. The majority of the studies in this SLR have this study purpose. Chin et al. (2017), for instance, proposed a diagnosis technique in which a number of machine learning classification algorithms were trained and tested to classify among 42 features, with the most significant 30, 28, and 26 features selected using a variety of feature selection techniques.

### 2.6.4 Data Profiling

This data extraction topic focuses on examining the research article's data profiles and establishing a connection between the study's data kinds and goals. Table 2.2 and Table 2.3 show the data profiling summary of the selected research articles. The table provides information about the data type, source, and volume of the articles and their frequencies as well as the table also divides them according to the research aim category. From the table, it is observable that mainly three kinds of data have been utilized to segment Ischemia with computer-assisted techniques.

#### 2.6.4.1 Dataset of CT and CTA images

The use of a computer-generated output as a helping tool for a physician making a diagnosis is known as computer-aided diagnosis (CAD).To build up a system or evaluate this system for the classification of brain ischemic stroke data is the main raw material. As a dataset, it can be CT, CTA, or MRI. In this section, This thesis tries to elaborate on datasets that could be used to establish this type of CAD.

For deep learning-based models, datasets are mainly classified into two portions, training datasets and testing datasets. Training data is the initial data used to train deep learning models. Deep learning algorithms are taught how to make predictions or identify patterns from training datasets by feeding them training datasets. The performance of a model during training is tested using the validation set, a set of data that is distinct from the training set. Once the model has been trained, it is put to the test using a specific set of data called the test set. An overview of the dataset modules is shown in Figure 3.5.

Deep learning typically needs a large amount of data. While deep learning has been employed for many medical image-related tasks with a similar amount of patient data, a bigger volume of data would significantly improve the model performance. MRI, CT, and CT angiography datasets are commonly applied in this area of research for the detection, classification, or segmentation of ischemic stroke.

In many hospitals, the use of computed tomography (CT) imaging for patients with stroke symptoms is an important step in the regression testing and diagnostic process. However, automated approaches have found it challenging to extract potentially quantifiable information due to the delicate expression of ischemia in acute CT scans. The Table 2.2 will discuss the datasets of Deep Learning Based automatic tools.

**Table 2.2:** Datasets for CT images

| Reference | Dataset | How many Subject | Train Images | Test Images | Image Dimension |
|---|---|---|---|---|---|
| Gautam and Raman (2020) | Collected from Himalayan Institute of Medical Sciences Dehradun, India. | Total 900 images (Ischemic 300, Hemorrhagic 300, and Normal 300) | 720 | 180 | 512 X 512 |
| He et al. (2016) | Collected from in the database of General Medical System HiSpeed TC | Total, 420 images ( 140 healthy brains, and,140 hemorrhagic and 140 ischemic) | 336 | 84 | 140 X 140 |
| Chin et al. (2017) | | 256 | 128 | 128 | 512 X 512 |
| Choi et al. (2017) | Training and Testing datasets are collected from two different institutions. | 1479 (Ischemic 681, Normal 798) | 1254 (Ischemic 573, Normal 681) | 225 (Ischemic 108, Normal 117) | 512 X 512 |
| Nishio et al. (2020) | Collected from Osaka Red Cross Hospital and Ichinomiya Nishi Hospital | 238 | 189 | 49 | 512 X 512 |
| Pan et al. (2021) | | 116 (ischemic), and 26 (normal) | 58 ischemic, 13 normal | 58 ischemic, 13 normal | |
| Shinohara et al. (2020) | | 35 (ischemic), 39 (Normal) | | | 1380 X 1100 |
| Wu et al. (2021) | Central Hospital of Minhang District, Shanghai, China and, Huashan Hospital | 251(ischemic) and, 26 (normal) | | | |

#### 2.6.4.2 Dataset of MRI images

DWI (diffusion-weighted imaging) and ADC (apparent diffusion coefficient) are the two main types of MRI. Water molecule motion is the basis for diffusion-weighted imaging, which offers details about tissue integrity. Diffusion-weighted imaging (DWI) is commonly considered a significant tool in the study of the central nervous system. It is considered useful for the detection of acute ischemic stroke and intracranial infections. Splitting the datasets into two sections such as training and testing is better for these types of deep learning models, it also helps to evaluate the model. In Table 2.3 Authors try to show the different types of public and private MRI datasets.

**Table 2.3:** Datasets for MRI images

| Reference | Dataset | (How many Subject) | Train Images | Test Images | Image Dimension |
|---|---|---|---|---|---|
| Chen Q et al.(2017) | SPES dataset and, tested on SPES and LHC datasets | (435 2D slices) | 1344 2D image slices | 90 2D image slices | |
| Mok and Chung (2017) | Obtained from IMS and SUM Hospital, Bhubaneswar, Odisha, India, | 267 images | 267 images | | |
| Zhao et al. (2021) | | 577 | 398 | 179 | |
| Zhang et al. (2018) | Sonata, Siemens Medical, Erlangen, Germany | 242 | 90 | 62 | |
| Do et al. (2020) | | 390 | 319 | 71 | |
| Gaidhani et al. (2019) | Data were obtained from ATLAS (Anatomical Tracings of Lesions after Stroke | 600 | 400 | 200 | 197 X 233 |
| Karthik et al. (2020) | ISLES 2015 | | ISLES 2015 | ISLES 2015 | 224 X 224 |
| Kumar et al. (2020) | ISLES 2017 | 75 | 43 | 32 | 256 X 256 |

#### 2.6.4.3 Image preprocessing of CT and CTA images

In medical image analysis, image pre-processing plays a significant role. To preserve image quality, different kinds of image processing are used such as image denoising, enhancement, contrast adjustment, and so many other techniques. Filters are so important in this area of pre-processing which is performed to achieve many requirements. This section will discuss various image-prepossessing techniques used in literature.

**Table 2.4:** Prepossessing techniques applied by the Authors for CT and CTA images

| **Reference** | **Image preprocessing Techniques** |
|---|---|
| Gautam and Raman (2020) | Contrast adjustment, Image Fusion, SWML, SMDG |
| Nishio et al. (2020) | Normalization, Horizontal flipping, Cropping, and Random rotation. |
| Pan et al. (2021) | Shift and rotation, Ellipse fitting |
| Shinohara et al. (2020) | Median filters, Gaussian filters, Flipping, Rotation |
| Wu et al. (2021) | Spm12, Rotation, Ellipse fitting |
| Chin et al. (2017) | Binarized by Otsu algorithm, Data Augmentation. |
| Castillo et al. (2021) | Image Fusion, FSL FLIRT |
| Alhelal et al. (2021) | ROI, Shifting, Rotation, Flipping |

Complex bone fractures and other bone and joint issues can be found by CT scans, which can also detect some cancers, benign (noncancerous) tumors, heart disease, blood clots, bowel disorders (blockages, Crohn's disease), diseases of the brain and spinal cord, and injuries.

A median filter was used to remove noise generated (Gaidhani et al., 2019). Gaussian is a linear filter. The image is typically blurred or the noise level is decreased. You can use them for "unsharp masking" if you use two of them and subtract (edge detection). By itself, the Gaussian filter will weaken contrast and blur edges. The FSL Brain Extraction Tool (BET) was used to remove the skull and non-brain tissue. The skull of a CT, CTA, and MRI is the non-stroke area, so removing the skull is useful for stroke detection (Stier et al., 2015). Chen Q et al. (2017) and Wu et al. (2021) use SPM12 software to convert DICOM format to the NIFTI format of the images. Multiple visuals are placed into a common statistical distribution in terms of size and pixel values during the image normalization process, which is frequently employed in the production of data sets to train the AI model. However, a single image can also be normalized within itself. Regularly, both spatial and intensity normalization are involved in the process. While the models were being trained, images were subjected to online image augmentation techniques such as horizontal flipping, cropping, and random rotation (Nishio et al., 2020). Table 2.4 referred to the details of preprocessing techniques of CT and CTA images.

#### 2.6.4.4 Image preprocessing of MRI images

MRI images play a significant role in the field of medical image analysis. For general imaging of soft tissues, such as the heart, brain, muscles, and malignancies, MRI is used. A specific form of MRI called DW-MRI measures the diffusion of water molecules in tissues. Water molecule diffusion inside tissues is measured using DW-MRI. This can highlight anomalies, especially in regions with limited water diffusion, including ischemia (impoverished blood flow) or tumor areas.

This section will cover a variety of image-prepossessing methods based on MRI images that have been utilized in various literature.

**Table 2.5:** Prepossessing techniques applied by the authors for MRI images

| Reference | Image preprocessing Techniques |
|---|---|
| Chen Q et al. (2017) | SPM12, Registration method, MRIcron software (BET2), Gaussian method |
| Do et al. (2020) | Cropping, contrast stretching, Histogram analysis, flipping, Gaussian filter |
| Gaidhani et al. (2019) | 3D image to 2Darray, Median filter, then Normalization |
| Kumar et al. (2020) | Normalization |
| Liu et al. (2021) | UNet BrainMask, in-plane (IP), Normalization |
| Stier et al. (2015) | FSL Brain Extraction Tool (BET) , Registration methods. |
| Yu et al. (2020) | Coregistered, Normalization, Reperfusion, Thresholding. |
| Zhang et al. (2021) | Median filter, N4 bias field correction, FSL BET, FSL FLIRT, Interpolation |
| Hu et al. (2020) | Cropping, Flipping |
| Bendiabdallah and Settouti (2021) | Flipping |

As an image preprocessing approach, various types of filters are applied for feature extraction. Normalization, flipping, registration, shifting, rotation, and many more image processing techniques are used to prepare an image for building up trainable or testable datasets of images. Table 2.5 illustrates the details of preprocessing of MRI images. The decomposition of data files such as CT, MRI, or CTA is an important element of image preprocessing, and most authors utilize the spm12 software to solve this issue.

### 2.6.5 Methodology

This data extraction theme focuses on the research methodologies that have been employed in the articles to autonomously segment Ischemia. Table 2.6 shows the list of major techniques or technologies that have been applied in the articles to achieve the goal.

**Table 2.6:** Methods and Performance analysis table

| Reference | DL method | Layer Information | Type of Data | Performance measure | | | |
|---|---|---|---|---|---|---|---|
| | | | | Accuracy(%) | Sensitivity | Specificity | DSC |
| Gautam and Raman (2020) | Image fusion, P_CNN | 2 convo, 2 FC, ReLU, Maxpooling, dropout, softmax | CT | 92.22 | 0.9222 | | 0.92 |
| Chen Q et al.(2017) | Otsu algorithm, CNN | 2 convo, 1 pooling a single FC, ReLU | CT | 92.969 | 0.9516 | 0.9090 | |
| Nishio et al. (2020) | Two-stage CNN, YOLOv3 and, VGG16 | | CT | | 0.373 | | 0.34 |
| Pan et al. (2021) | ResNet, Maximal connected region (MCR), Maximum a posteriori probability (MAP) | | CT | 89.71 | 0.8817 | 0.9125 | |
| Shinohara et al. (2020) | DCNN | | CT | 86.5 | 0.829 | 0.897 | |
| Wu et al. (2021) | U-net, ResNet, Maximum a posteriori probability (MAP) | | CT and MRI | 85.71 | 0.8431 | 0.8462 | |
| Chen L et al.(2017) | Res-CNN | 10 convo 4 residual, 4 concate 4 deconvo BN LReLU. | MRI | | | | 0.74 |
| Zhao et al. (2021) | Multi feature map fusion network ,VGG16 | Convo, BN, ReLU, MaxPooling, GAP, FC, Sigmoid | MRI | | | | 0.65 |
| Zhang et al. (2018) | (FC DenseNET) | | DWI | | 0.7815 | | 0.89 |

**Table 2.6:** Methods and Performance analysis table (cont.)

| Reference | DL method | Layer Information | Type of Data | Performance measure | | | |
|---|---|---|---|---|---|---|---|
| | | | | Accuracy(%) | Sensitivity | Specificity | DSC |
| Do et al. (2020) | RRCNN, ( VGG16 + ResNet) | Convo, MaxPool, FC, Softmax | DWI | 87.3 | 0.839 | 0.90 | 0.89 |
| Gaidhani et al. (2019) | (LeNet, SegNet) | Convo, max-pool, FC | DWI | 98.94 | 0.97 | | 0.97 |
| Karthik et al. (2021) | FCN | Conv, DeConv, Dropout, Softmax. | DWI | | 0.8009 | 0.9457 | 0.78 |
| Kumar et al. (2020) | CSNet | convo, ReLU, MaxPool | DWI | | 0.89 | | 0.83 |
| Liu et al. (2020) | DRANet | convo, MaxPool, Sigmoid, Residual | MRI | 94.04 | 0.9404 | | 0.76 |
| Liu et al. (2021) | DAGMNet, UNet | DAG, cAG , sAG, Maxpool, Conv. | DWI | | 0.73 | | 0.76 |
| Sovetkin et al. (2020) | DeepMedic | | CTA | | 0.93 | 0.82 | |
| Nishio et al. (2020) | (3D-CNN model) | | CTA | | 97.3 | 74.7 | |

In this section, the different architectures were reviewed of deep learning models that are used to classify ischemic brain strokes and try to analyze their performances in Table 2.6.

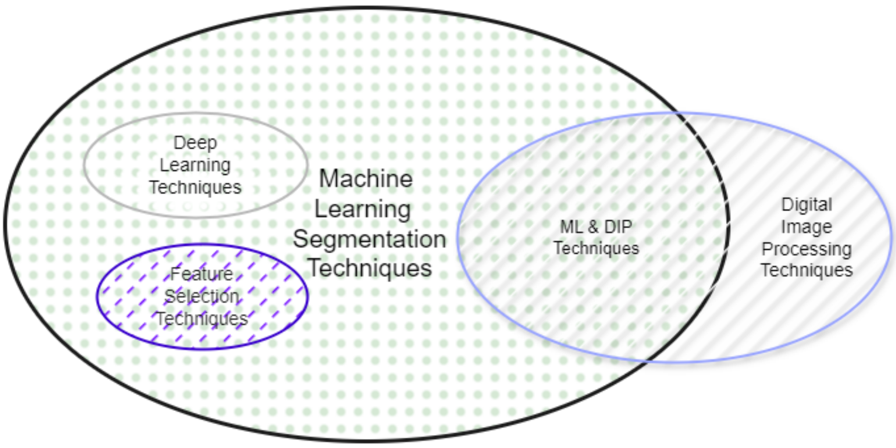


**Fig. 2.12.** Ven Diagram of applied research methodologies

**Deep learning methods used CT images** A new classification strategy based on image fusion and deep learning is presented in this research (Gautam and Raman, 2020). To improve the contrast of the stroke region, the fusion method was employed. Later, a novel CNN architecture was presented for classifying brain stroke into two (hemorrhagic and ischemic) and three (hemorrhagic, ischemic, and normal) categories using CT images. Chin et al. (2017) proposed CNN module, contains one fully connected layer, one max-pooling layer, and two convolutional layers, is used. In this study, they trained and evaluated a CNN module that could be detected an ischemic stroke using 256 patch images. Nishio et al. (2020) wanted to develop and test automatic Ischemic Stroke detection system using a two-stage deep learning model. A board-certified radiologist assessed the test set head CT scans with and without the detection model to assess the detection model's outcome. Pan et al. (2021) tried to explore the recognition information of the acute ischemic stroke infarct core on non contrast CT images using a deep learning residual network and two optimization approaches, which have a distinctive and crucial diagnostic value. The goal of this research (Shinohara et al., 2020) was to create a deep learning-assisted interactive method for identifying the hyperdense middle cerebral artery (MCA) sign on non-contrast computed tomography (CT) in patients with acute ischemic stroke. To categorize input visuals as AIS-positive or AIS-negative, a deep convolutional neural network (DCNN) was employed. In this study, (Wu et al., 2021), a novel two-stage CNN method for accurately identifying ischemic stroke on non-contrast CT images has been reported. Several trials have shown promising results.

**Deep learning methods used MRI images** Using multi-modality MRI sequences, the Res-CNN (Chen L et al., 2017) network is employed to segment acute ischemic stroke lesions. When compared to the six traditional CNN approaches, it performs better. Res-architecture CNN's is primarily U-shaped. Up-sampling operators were employed in U-shape architecture to replace unspooling operators, while skip connections were utilized to directly connect opposing contracts. The model's loss rate can be significantly lowered, thereby increasing performance.

Zhao et al. ( 2021) developed a DL based method titled multi-feature map fusion network (MFMF-Network) based on two types of subjects: weakly labeled subjects are trained for classification, and fully labeled subjects are tuned for segmentation.

DenseNets significantly surpassed ResNets when they were originally introduced for the categorization of 2D natural photographs due to their novel dense connection model. These qualities are needed, especially in healthcare applications where training datasets are frequently smaller and data dimensionality might be larger. Zhang et al. (2018),developed and make use of DenseNet's capacity to segment crisp strokes in 3D space. Comparative experiment findings show that the approach is superior to other cutting-edge 2D or 3D CNN models. Diffusion-weighted imaging was used in (Do et al., 2020) to construct a DL model for automatic binary categorization of the Alberta Stroke Program Early Computed Tomographic Score (ASPECTS) in acute stroke patients (DWI). Gaidhani et al. (2019) used the categorization and segmentation of pictures of brain strokes (AIS). LeNet and auto encoder decoder were the two DL models they used for classification and segmentation. They will try to improve the segmentation algorithm's precision and identify the precise location of the brain stroke by utilizing a variety of powerful deep-learning pre-trained models.
Karthik et al. (2020) design a method for segmenting ischemic lesions was proposed by using multi-scaled encoded feature maps, and the ROI align-based patch CNN constructs a multi-level deconvolutional ensemble. This technique efficiently develops dense, reliable, pixel-class discriminatory feature representations at the encoder blocks.

Kumar et al. (2020) used a multi-hybrid model of the Fractal Net and U-Net combining the best aspects of both models and adds denser feature retrieval layers at the encoder.

The segmentation process is split into a Classifier and a Segmenter in the model. Kurgan-et al. (2020) proposed DRANet, a new deep-learning architecture featuring an attention module. DRANet has developed to segment ischemic stroke and WMH lesions accurately. In their independent testing dataset, the suggested model DAGMNet (Liu et al., 2021) outperformed generic models like UNet and FCN, as well as DeepMedic. This strategy presented a low rate of false-positive detection while being noticeably better at segmenting tiny lesions, which was a key issue for earlier techniques

### 2.6.6 Research Findings

While the chosen studies for this systematic literature review yielded a variety of study outputs, their primary objective was to use computer-assisted methodologies to segment Ischemia. The study's conclusions can be summed up as follows: a subset of important characteristics for identifying ischemia; computational assessment and validation of the suggested method; comparison with other algorithms or current approaches; architectural framework; theoretical validation; and website/mobile application. The majority of the publications presented a study's findings together with a computational assessment and validation of the suggested methods; they first suggested a method for Ischemia segmentation, which they subsequently assessed and verified using a variety of performance metrics using train and test datasets. After that, in order to investigate the effectiveness of the suggested technique, a computational assessment using training and test datasets of brain pictures was carried out. Additionally, a sizable collection of publications offered a comparative study of different kinds of machine learning classifiers with the goal of identifying the most effective one or demonstrating a comparison between the suggested computational method and the manual Ischemia diagnosis procedure. Furthermore, a subset of the most important features for Ischemia segmentation were proposed as study findings by some research employing a dataset of patients' diverse clinical and metabolic symptoms; and lastly, a set of features as research outcome that offers optimal accuracy when utilizing machine learning models. An additional set of research provided experimental use of their suggested techniques for

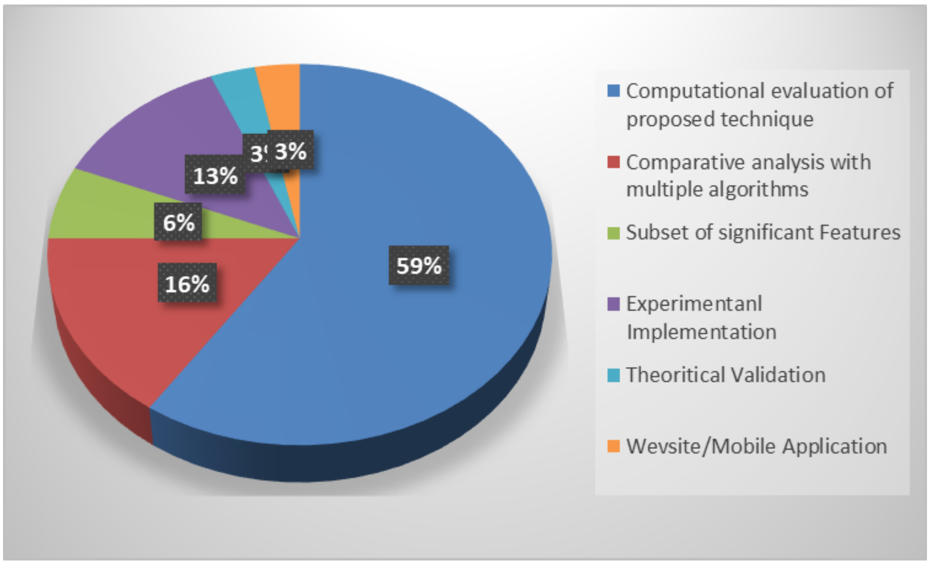


**Fig. 2.13.** Various type of research outcomes

Ischemia segmentation from images. A few studies produced a model as study outputs to automatically identify ischemia using machine learning-based approaches for web-based or mobile apps.

### 2.6.7 Reporting the Review

#### 2.6.7.1 Summarizing Review Findings

This systematic literature review (SLR) has examined thirty-two pertinent studies, all of which have used computer-assisted methodologies to segment ischemia in the human brain autonomously. Six data exploration topics have been used in the data synthesis process to analyze the articles methodically. Below is a quick summary of the conclusions drawn from each of the themes.

- The initial theme's word clouds under topological association show that the majority of the articles mention Ischemia segmentation techniques in their titles or keywords and that the titles and keywords of the selected studies are closely associated with one another with several similar and frequently used words.

- According to the research profiling of the papers, several publishers have shown nearly equal interest in publishing this field of study in journals and conferences. The publication data broken down by year demonstrates the growing interest of scholars in this field. Therefore, the data shows that the autonomous segmentation of Ischemia utilizing computer-assisted methodologies and machine learning is becoming more and more popular among academics globally. Nonetheless, the author's original data show that the bulk of the research is from India and that the majority of them have been carried out on the South Asian subcontinent. A few researchers have also received funds to carry out this sort of study.

- Examining the scopes of the chosen research papers, it has been discovered that, while the primary objective of all the publications is to segment Ischemia using computer-assisted approaches, each one also has specific, unique study aims.

- The data profiling analysis of the articles indicates that there is mainly one type of data that has been utilized for Iscemia segmentation: which is patients' Brain Image data CT, MRI, or CTA.

- According to the research approaches used in the publications, this field has mostly used four types of technologies: deep learning, machine learning, digital image processing, and feature selection techniques. The majority of these investigations used several kinds of machine learning classification models, including DT, SVM, KNN, and random forest. Additionally, the publications have used a variety of feature selection strategies to investigate the most important characteristics for Ischemia segmentation. Deep learning methods, however, are widely applied in this field.

- The last step involved grouping the findings of the chosen papers into six primary categories. It was noted that the majority of the publications presented research outputs including computational assessment and validation, as well as a comparison of the suggested methodologies with other approaches. Numerous research works have employed diverse performance criteria to assess the effectiveness of their recommended techniques. It has also been observed that, despite the usage of comparable classifier types in several publications, the methods of implementation and data pre-processing adopted by each article resulted in varying performance gains.

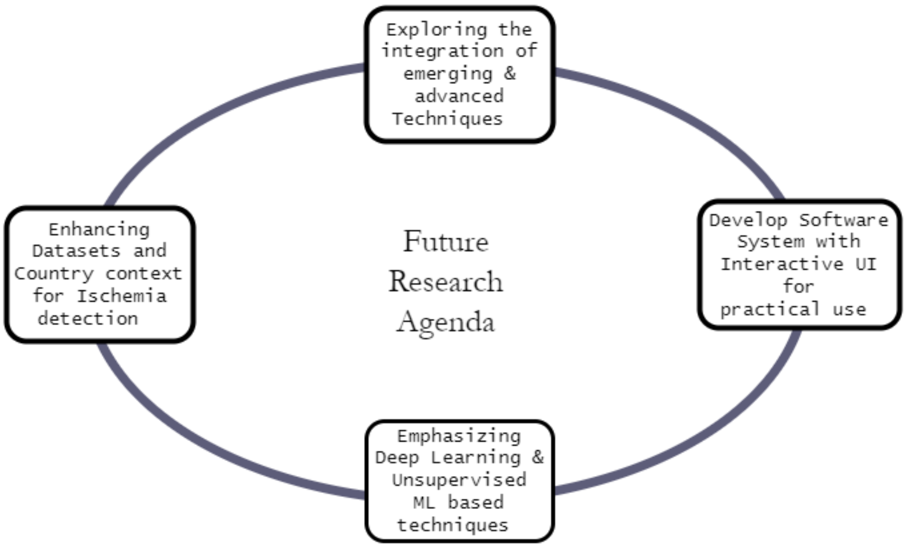


**Fig. 2.14.** Outline for future research agenda

#### 2.6.7.2 Research Gaps and Future Research Recommendations

The results of this systematic literature review (SLR) indicate potential research gaps or limits in the field of Ischemia segmentation using computer-assisted approaches. It also offers future research topics for more effective procedures. The proposed research projects listed below may be considered in the future to close the gaps in the literature. A quick summary of the potential study program is shown in Figure 2.14.

Based on an analysis of previous methods, this study acknowledges that many segmentation techniques encounter challenges in achieving accurate results due to limited data availability, and a significant number of these methods overlook the importance of considering the z-axis feature. Most approaches primarily rely on the fundamental principles of deep learning, which makes it difficult to effectively extract features related to stroke areas given the complex characteristics of brain lesions. To address these issues, the focus of this study is on utilizing 3D UNET, as It is trainable effectively even having a constrained number of data while also preserving the features along the z-axis. In addition, the modules of inceptionv3 are chosen for extracting features from brain lesions, as its various kernel sizes make it well-suited for this purpose.

**Challenges with the dataset:** In general, obtaining data for this research topic is a difficult undertaking. Only two authors used publicly shared datasets, while the majority of the researchers used private databases, according to this review. Kumar et al.(2020) developed a deep learning framework for ischemic stroke lesion segmentation in 2020, using ISLES 2017 DWI data to train and evaluate their CSNet model. SPES is another online MRI dataset that was used by Chen Q et al. (2017) to train model, with LHC datasets used for testing. As far as it is known, these three MRI datasets are accessible; nonetheless, most researchers rely on their private datasets gathered from other hospitals. After reviewing most of the current work in this field, it has been concluded that anyone who wants to work should be concerned about datasets.

### 2.6.8 Chapter Summary

This systematic literature review thoroughly examines the existing relevant studies that focus on the use of various computer-assisted methodologies for Ischemic Stroke segmentation in order to explore state-of-the-art viewpoints, identify shortcomings, and identify potential areas of future research. Using specific inclusion-exclusion criteria and the PRISMA approach, the pertinent publications have been carefully chosen. The aim, objectives, and publication histories of the previous studies pertinent to the segmentation of ischemic stroke have been examined to fulfill the first research objective (R01). To fulfill the second research objective (RO2), an investigation has been conducted into the data sources, kinds, and qualities that have been used in the reviewed studies about their relevance to study scopes. To achieve the third research goal (RO3), the SLR also looked at various computer-assisted techniques, algorithms used in various studies, and assessment strategies that have been used to automatically diagnose ischemic stroke. In addition, the study has outlined the overall conclusions from the data synthesis from a few chosen studies as well as the research gap to satisfy the fourth research objective (RO4). To satisfy the fifth research objective (RO5), several recommendations have been made about potential future study areas in the realm of autonomous Ischemic detection with greater efficiency.

This literature review has a flaw in that it may exclude some pertinent and significant publications due to specific exclusion-inclusion criteria. For example, some publications may not be eligible for consideration because their entire text is unavailable or was written in a language other than English. Furthermore, the predefined list of lists of keywords used in the article search may exclude certain related articles. In the future, the authors of this study want to conduct a more comprehensive evaluation that will include clinical studies about ischaemic stroke in addition to more recent, relevant scientific publications. As a result, there is a wide range of potential research topics in this field. The results of this review will surely help academics comprehend the scope and depth of previous studies, as well as the prerequisites and constraints for carrying out additional experiments and studies for ischemic segmentation in the future. Furthermore, this SLR will support academics and medical practitioners in discussing the value of various computer-assisted methods, including image processing and machine learning, in real-time decision-making for early sickness identification.

# CHAPTER 3

## METHODOLOGY

This chapter discusses the Ischemia segmentation procedure with an ensemble deep-learning technique using patients' Brain image data. Firstly, the chapter includes the materials and methods for the proposed methodology, which has been subdivided into several modules: Inception, and UNET. Secondly, the chapter describes the exploration of deep learning techniques which includes the methodology those are applied in this part of the thesis: traditional DL, traditional DL with feature reduction, deep learning technique, and finally the proposed Ensemble DL technique.

### 3.1 Deep Learning Architecture

Deep learning has revolutionized image segmentation by providing powerful algorithms capable of automatically identifying and delineating objects within images. In deep learning approaches, two components comprise the generalized semantic segmentation network: an encoder and a decoder. An arbitrarily high-dimensional image's information content is compressed by the encoder into a feature vector. The encoded features are gradually upscaled by the decoder to the original resolution (Sovetkin et al., 2020). Fully Convolutional Networks (FCNs) (Chen L et al., 2017) are one of the pioneering architectures specifically designed for semantic segmentation tasks. Unlike traditional convolutional neural networks (CNNs) that end with fully connected layers, FCNs replace these layers with convolutional layers to retain spatial information. FCNs perform pixel-wise classification, outputting dense prediction maps that correspond to different object classes. U-Net (Ronneberger et al., 2015) is a convolutional neural network architecture designed for biomedical image segmentation but widely used in other domains as well. It consists of a contracting path (encoder) for capturing context and a symmetric expanding path (decoder) for precise localization. U-Net incorporates skip connections between corresponding encoder and decoder layers to facilitate the flow of high-resolution features. DeepLab (Chen et al., 2017) is a series of convolutional neural network architectures designed for semantic image segmentation. It utilizes atrous (dilated) convolutions to effectively enlarge the receptive field without increasing the number of parameters. DeepLab also incorporates multi-scale feature fusion techniques, such as atrous spatial pyramid pooling (ASPP), to capture contextual information at multiple scales. Mask R-CNN (He et al., 2017) extends the Faster R-CNN object detection framework to perform instance segmentation, which involves not only detecting objects but also delineating their boundaries at the pixel level. Mask R-CNN generates bounding boxes and segmentation masks simultaneously using a region proposal network (RPN) and a parallel branch for mask prediction. PSPNet (Pyramid Scene Parsing Network) (Zhao et al., 2017) is a deep-learning architecture for scene parsing, which involves segmenting an image into various semantic regions. PSPNet incorporates a pyramid pooling module to capture global contextual information at multiple scales. This module aggregates features from different pyramid levels, enabling the network to make more informed segmentation decisions.

### 3.1.1 Inception

A typical CNN network is made up of the input, convolutional, pooling, fully connected, and output layers, among other parts. These segments work together to process and extract features from images, enabling the CNN to effectively recognize patterns and objects within the given data. The Inception journey was initiated by the Google team in 2014 with the introduction of the GoogleNet framework. Inception modules are a key component of the Inception architecture, which was introduced by Google in the paper "Going Deeper with Convolutions" by Szegedy et al. (2015). This framework sought to decrease the number of parameters while concurrently deepening the network. It has therefore been extensively used in imagining classification tasks. GoogLeNet has evolved with several variants, including Inception V1 (Szegedy et al., 2015), Inception V2 & V3 (Szegedy et al., 2016), and inception V4 & Inception-ResNet (Szegedy et al., 2017). These variants have contributed to the continuous development and refinement of the Inception architecture. Within a neural network, the main goal of the Inception modules is to effectively collect features at various spatial scales. Convolutional layers in conventional convolutional neural networks (CNNs) frequently have set filter sizes, which may make it difficult to collect information at various scales. On the other hand, Inception modules process the input concurrently by combining filters of varying sizes (1x1, 3x3, 5x5). As a result, the network may record characteristics at different abstraction levels. Typically, the Inception module comprises concatenating the outputs of parallel convolutional branches when they have finished. Furthermore, to regulate the number of input channels for the bigger convolutions and save computing costs, 1x1 convolutions are frequently included before larger convolutions. The network can efficiently learn to capture both small details and high-level characteristics by combining different filter sizes in parallel. Because of its capacity to build complex hierarchical representations, this architecture has demonstrated remarkable performance in a variety of deep learning tasks, such as semantic segmentation, object recognition, and image classification.

**InceptionV1:** The team at Google unveiled InceptionV1 (Szegedy et al., 2015), sometimes referred to as GoogLeNet, in 2015, marking a significant advancement in deep learning architecture. It is distinguished by the novel Inception module, which efficiently captures information at many scales by using parallel convolutional filters of varying sizes (1x1, 3x3, 5x5). Its performance is further improved by using 1x1 convolutions to reduce dimensionality, global average pooling in place of fully connected layers, and auxiliary classifiers at intermediate levels during training. Using methods like batch normalization and auxiliary classifiers, Inception v1 generates deep network topologies without experiencing overfitting or vanishing gradients while retaining computing efficiency through the use of 1x1 convolutions. For picture categorization, its performance in the 2014 ImageNet Large Scale Visual Recognition Challenge (ILSVRC) confirmed its efficacy.

**InceptionV2:** Google researchers introduced the original Inception architecture. Inception v2 (Szegedy et al., 2016), commonly referred to as ”BatchNorm Inception,” is an improvement that includes many improvements to increase training efficiency and performance. The integration of batch normalization layers to speed up and stabilize training factorized 7x7 convolutions to control computational complexity while maintaining expressive power, label smoothing regularization to prevent overfitting by boosting model confidence, efficient strategies for grid size reduction to increase computational efficiency, and additional training methods like stronger data augmentation and smaller learning rates for improved stability and convergence are some of the key features. Inception v2 addresses the shortcomings of its predecessor while building upon its strengths overall, producing a more effective and efficient deep learning architecture that is extensively used in computing.

**InceptionV3:** The Inception module is typically composed of three convolutions of varying sizes, along with a maximum of one pooling operation. Following the convolution process, the output channels from the previous layer are combined for network output, and nonlinear fusion is applied. This approach helps prevent overfitting while enhancing the network's expressiveness and adaptability at multiple scales. By incorporating convolutions of different sizes and pooling them strategically, the Inception module enables effective feature extraction and improves the overall performance of the network. The Inception modules used to replace the traditional convolutional layer are one innovative feature of InceptionV3. The inceptionV3 (Szegedy et al., 2016) module's ability to extract features using various kernel sizes is the primary distinction between the inception module's concept and traditional convolutional neural networks. There are three different kinds of Inception modules, according to their architecture: Inception A, Inception B, and Inception C. The GoogleLeNet inception module's equivalent is Inception A, that is to say, factorization into smaller convolutions, which means they divide the more extensive convolutions into smaller ones (like, instead of 5x5 convolutions, they use two 3x3 convolutions). In InceptionB, they used spatial factorization into Asymmetric Convolution, which means instead of 7 x 7 convolution, use 7 x 1 and 1 x 7 convolutions. To support high-dimensional representations, Inception C uses many kernels of various sizes. Inception C has kernel sizes of 1x1, 1x3, 3x1, and 3x3. This architecture can lower computer expenses while significantly increasing computing efficiency.

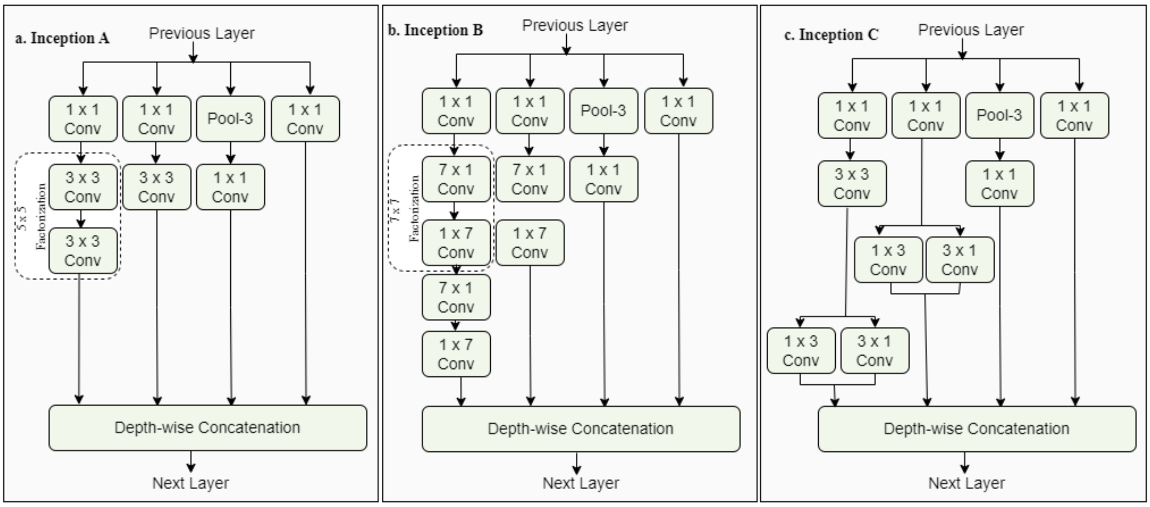


**Fig. 3.1.** Inception module of InceptionV3

### 3.1.2 U-Net

Although it has been widely developed for several other segmentation applications as well, the U-Net architecture is a convolutional neural network (CNN) architecture created for biomedical image segmentation tasks. Ronneberger et al. (2015) presented in their publication, "U-Net:Convolutional Networks for Biomedical Image Segmentation." U-Net utilizes an encoder-decoder architecture in which a sequence of convolutional and pooling layers are used by the encoder to extract high-level features from the input picture, and the decoder progressively upsamples these features to create a segmentation mask. Skip connections between corresponding encoder and decoder layers are incorporated by U-Net. These skip connections concatenate feature maps from the encoder directly to the decoder, enabling the network to maintain spatial information and capture fine-grained features. Convolutional layers and max-pooling layers make up the encoder path, also known as the contracting path, which gradually reduces the feature maps' spatial dimensions while deepening them. Transposed convolutional layers make up the decoder route (expanding path), which upsamples the feature maps to the original input size while progressively decreasing their depth. Usually, a 1x1 convolutional layer and a softmax activation function are used in the last layer of the U-Net architecture to create the segmentation mask. A dense prediction map with each pixel representing the expected class probability is the network's output. To improve the model's resilience, U-Net frequently uses data augmentation methods including flips, random rotations, and elastic deformations. Moreover, dropout regularization may be used to stop overfitting during training.

**3D U-Net:** Based on the concept of 2D Unet, Çiçek et al. (2016) design & develop a 3D-U-Net architecture to enrich the spatial information available to the U-Net architecture. To enable 3D operations, the entire operation of the network has been modified. The system depends on the original U-Net design and utilizes an expanding decoder after a developing encoder to achieve full-resolution segmentation. This development's framework receives volumes in three dimensions as data and treats individuals with the proper three-dimensional actions. 3D U-Net was mainly employed to detect vascular boundaries (Kleesiek et al., 2016). The original model utilized in this research is a 2D CNN named HED (Holistic Edge Detection (Xie and Tu, 2015). The investigators added an extension path to the network's topology to address HED's weak localization power for the tiny vascular items. Also, 2D-Unet had weak localization power to detect small vascular objects; in this way, 3D-Unet could also overcome this shortcoming.

**3D vs 2D:** The utilization of three-dimensional information in the data can potentially improve the performance of the model. The segmentation responsibilities for 2D and 3D images differ in several aspects. The inclusion of the Z-axis as a feature in 3D data provides additional intelligence. Knowledge increases more valuable the more z-axis fragments are employed. Compared to other models, a simulation based on three-dimensional convolution often requires more parameters and is more challenging to train. The 3D model necessitates a larger training dataset to prevent overfitting. In 2D images, certain disorders may not exhibit noticeable symptoms, whereas, in 3D space, abnormalities can be detected. Due to the presence of sparse three-dimensional structures and a limited receptive area in some disorders, a 2D network might function more effectively. MRI data contain valuable information about the z-axis since cerebral vascular occlusion is an essential component responsible for ischemic stroke, and the area of damage extends into three dimensions.

## 3.2 Proposed Ensemble Deep Learning Method

U-Net is an optimized semantic segmentation method that was built based on FCNs (fully convolutional networks), which are composed of two parts. Feature extraction is done by its first part, and the other part is responsible for up-sampling. The decoder seeks to return this information to the original pixel position by upsampling the image using transposed-convolution layers. Rather than using U-Net's standard encoder, it is replaced (Fig 3.2) with the inceptionV3 layers, and the max-pooling layers are reassigned with the inception's novel hybrid of Hartley spectral pooling.

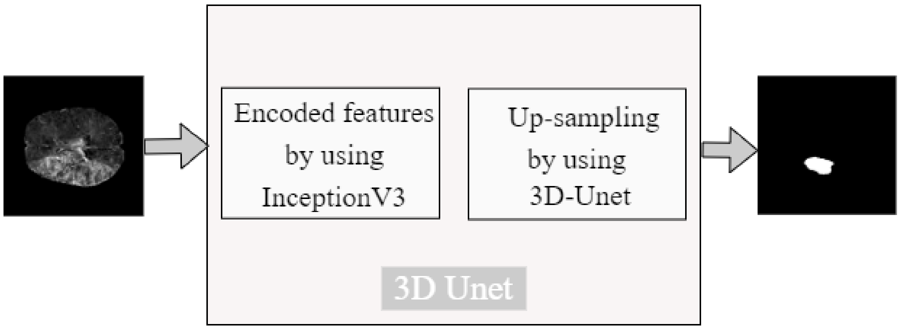


**Fig. 3.2.** Proposed basic Structure of the Model

### 3.2.1 Feature Extraction

The Original UNet's encoder part is replaced by the InceptionV3 and it is employed to extract features from MRI images. Because UNet's encoder has a fixed-size kernel it may not be as effective as InceptionV3 in capturing fine-grained local details, which are crucial for segmenting small or subtle anatomical structures. In the preceding section section 3.1.1 and Fig 3.1, the advantages of InceptionV3 have been established, particularly its superior feature extraction capabilities for such datasets. During the contracting path (Fig 3.3), the input image is progressively reduced in height and width but increased in the number of channels. It takes 256 X 256 X 32 dimensions images and as the network advances down the path, the increase in channels enables it to collect high-level information.

### 3.2.2 Up-sampling

The expansion path (Fig 3.3) takes the feature map from the bottleneck and resizes it to match the original input's size. Upsampling layers are used for this, increasing the feature map's spatial resolution while decreasing its number of channels. The decoder layers employ the skip connections from the contraction path to locate and enhance the image's characteristics. In the end, a label corresponding to a specific item or class in the input image is represented by each pixel in the output image. The output map in this instance is a binary segmentation map, meaning that every pixel denotes either the background or the foreground.

Inceptionv3 is a well-known deep-learning network that is designed to solve classification problems with high accuracy and less computational complexity. Choosing a fixed kernel size for image analysis can be challenging because the size of the characteristics can change. Because of this, heavier kernels are recommended for detecting global features, and lower kernels are favored for detecting area-specific features; fortunately, inceptionv3 implements these various size kernel notions.

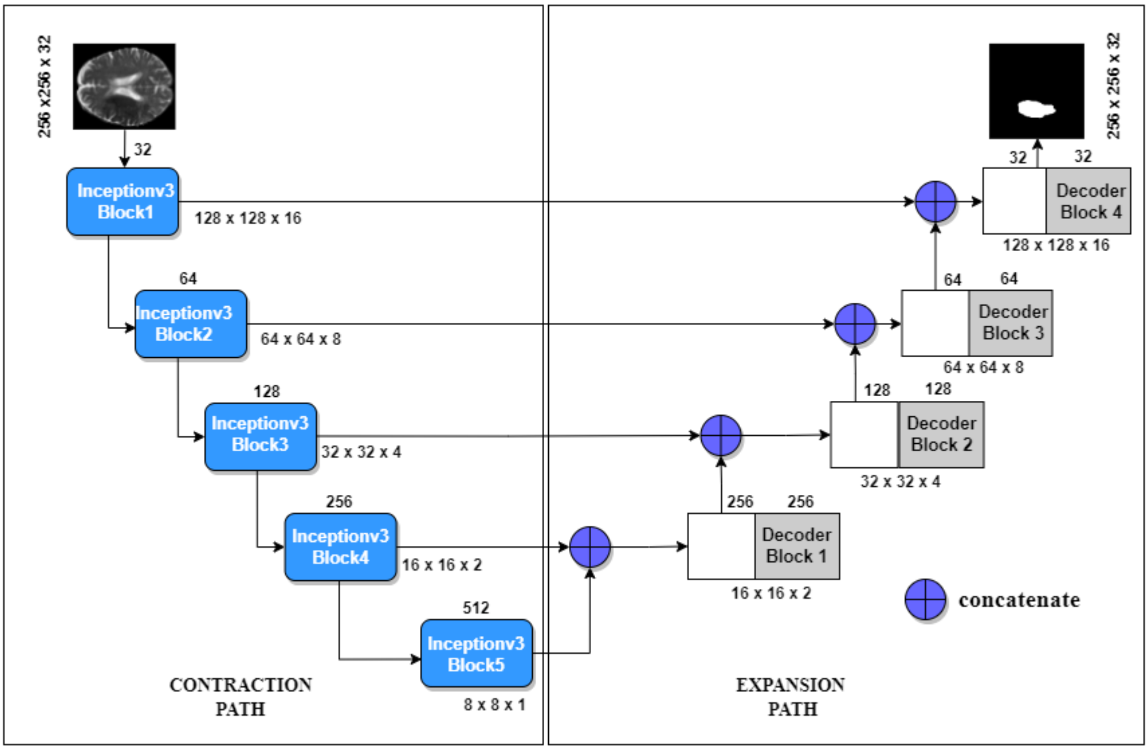


**Fig. 3.3.** Proposed Architecture

### 3.2.3 Vanishing Gradient and Overfitting

Researchers encounter two significant challenges when training a deep-learning model: overfitting and the vanishing gradient problem. The Vanishing-Gradient Problem is a difficulty in neural network training when the curves, or derivatives of the inaccurate coefficient concerning the parameters of the network, get progressively smaller as they go backward through the network.

In binary segmentation tasks, such as Ischemic stroke segmentation, the challenges become more pronounced and critical. When a mathematical framework successfully replicates the regularities and patterns seen in the data set of training but finds it difficult to generalize to instances of the problem that have not yet been addressed, this is known as overfitting. While it has been demonstrated that deeper networks tend to exhibit improved efficiency, they often encounter the challenge of gradient propagation, where the signal (gradient) (Kamnitsas et al., 2017) either amplifies or diminishes, hindering effective backpropagation of the overall loss to the lower layers. In 3D models, this problem becomes more pronounced. The classifier, the upgraded inception unit, and the basic convolutional layer are the three unique components of the Inceptionv3 model. To extract features, the convolutional block is utilized, with an alternative combination of convolutional and max-pooling. The enhanced inception module, inspired by the network-in-network architecture, concatenates the outputs of each branch's convolution while simultaneously performing multiple-scale convolutions. The inclusion of auxiliary classifiers improves gradient convergence, enhances training consistency, and effectively addresses overfitting and vanishing gradient issues (Lin et al., 2019). The measurements have specifically demonstrated that this strategy effectively balances performance and execution time by minimizing the maximum number of non-trainable parameters, thereby aiding in overcoming overfitting.

### 3.2.4 Dataset

The ISLES-2017 dataset is a specific version of the ISLES (Ischemic Stroke Lesion Segmentation) dataset released in 2017 on the website of (ISLES Challenge, 2017). This dataset is designed to facilitate research in the area of ischemic stroke lesion segmentation, particularly through the use of advanced machine learning, deep learning, and image processing techniques.

The ISLES-2017 dataset typically consists of DWI (Diffusion-weighted imaging) scans of the brain from patients who have experienced ischemic stroke. These scans are often accompanied by annotations or ground truth data that provide information about the location and extent of ischemic lesions within the brain. Such annotations are crucial for training and evaluating algorithms designed to automatically segment or identify these lesions in new DWI scans.

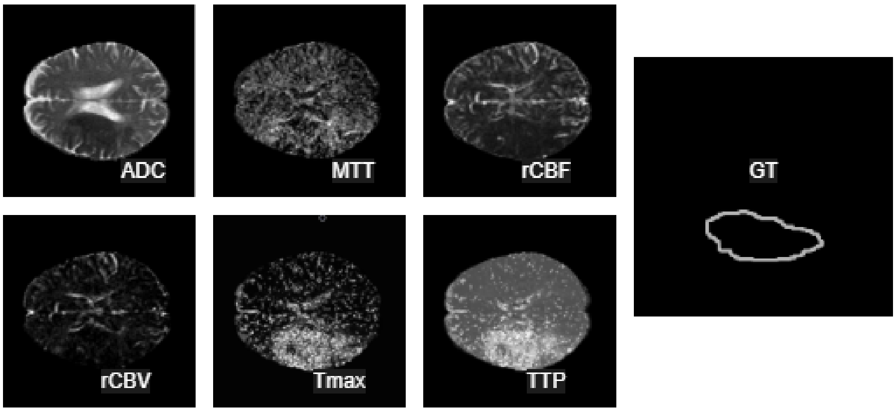


**Fig. 3.4.** Visualization of Dataset

The original ISLES-2017 dataset included a total of 450 MRI scans of individuals with ischemic stroke who were split into two groups: 370 subjects for training and 80 subjects for testing. Only the training dataset has ground truth annotations; the testing dataset is not provided. Still, fortunately, the Authors were able to acquire the ground truth from the testing datasets by following some processes on the online platform of the ISLES challenge. Six MRI acquisitions are offered for each subject: ADC, TTP, MTT Tmax, rCBV, and rCBF. For training this model, 350 cases were used, while 20 subjects made up the validation set from the ISLES 2017 dataset.

Researchers and practitioners in fields such as medical imaging, neurology, and machine learning often utilize datasets like ISLES-2017 to develop and validate new methodologies for stroke diagnosis, prognosis, and treatment planning. These datasets play a vital role in

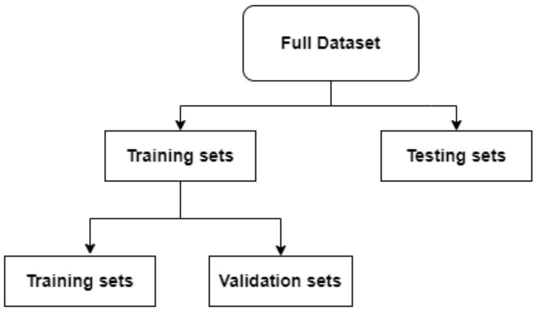


**Fig. 3.5.** Procedure of splitting dataset

advancing medical research and improving patient care in the field of stroke management.

### 3.2.5 Pre-processing

In this work, the datasets have been critically analyzed and preprocessed before being them into machine learning models to address the flaws and irregularities in the datasets such as missing or contradictory data samples, inconsistencies, noise, and other issues. The following steps have been employed for preprocessing the dataset:

The ISLES 2017 dataset provides six MRI parametric maps for each patient, including ADC map, rCBF, rCBV, MTT, TTP, and Tmax, which combine diffusion and perfusion information. The skulls of all imaging modalities have already been stripped and co-registered. MRIs are acquired from several hospitals; as a result, various sets of configurations were used to acquire the perfusion and diffusion maps. Because of this, scaled all maps for each patient to a standard volume by using the Minmax scaler, and after that, then resized all the maps with common dimensions of 256x256x32. By scaling, we transform all the maps into the [0,255] range, and at the end of the pre-processing, after combining all six maps into a single six-channel-based 3D volume. This is one kind of binary segmentation, and because of this, we labeled ground truth as two classes: class 0 for background and class 1 for Ischemic stroke area. For boost-up mathematical calculations, MRI maps, as well as ground truths, are converted into numeric arrays.

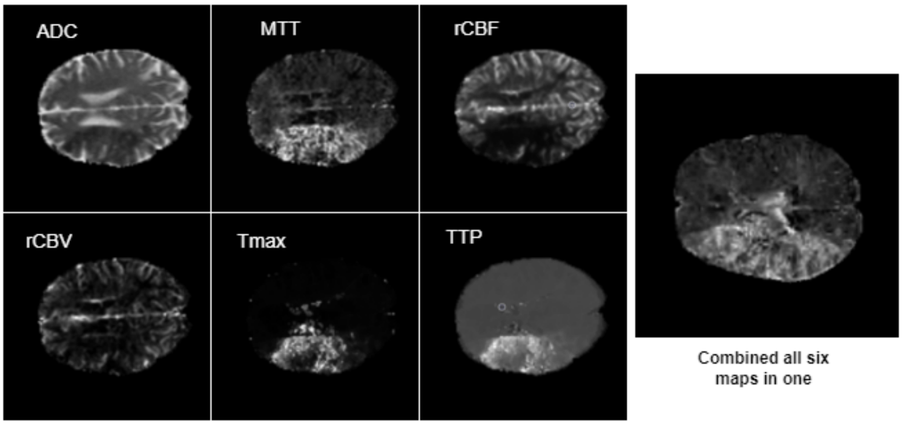


**Fig. 3.6.** Images maps after pre-processing

### 3.2.6 Evaluation matrix

Various popular performance measures are applied in deep learning methods. To evaluate a segmentation model, IoU (Intersection-over-Union), DSC (Dice-similarity-coefficient), Recall, Precision, and Accuracy perform better than others. Intersection-over-Union, or IoU is a statistic utilized in machine learning to evaluate the effectiveness of artificial intelligence algorithms by calculating how closely a predicted mask or bounding box resembles real-world data. A statistical tool used to compare two data sets is called the Dice similarity coefficient. This index is now possibly the most widely used instrument for evaluating AI-based picture segmentation methods. A recall is determined by calculating the ratio of correctly recognized tested items to all favorable samples. The formula is used, total-loss = dice-loss + (1 * focal-loss) to compute total loss. Let's assume that the values of True Positive, True Negative, False Positive, and False Negative are denoted as W, X, Y, and Z, respectively. Then, the measurements can be explained by the following mathematical functions:

$$Accuracy = \frac{W + X}{W + X + Y + Z}$$

$$IoU = \frac{W}{W + Y + Z}$$

$$DSC = \frac{2W}{2W + Y + Z}$$

$$Recall = \frac{W}{W + Z}$$

$$Precision = \frac{W}{W + Y}$$

### 3.2.7 Hyper-parameters

Different kinds of hyperparameters are used in this study. During the training of this model, the Adam-Optimizer is utilized with a learning rate of 0.00001. For training, this model uses a small batch size of two batches because one subject has six channels, which is basically a large amount of data incorporated into one subject, so a small batch size is effective for those types of datasets. The implementation was done in TensorFlow and Keras. And the whole experiment was done on the Google colaboratory platform because of the limitations of the physical GPU. For each prediction, it took around seven seconds.

## 3.3 Phases of Ischemia segmentation using MRI

In this study, the proposed ensemble deep learning segmenter has been Implemented, trained, and tested using the patient's most significant set of MRI data. A framework of the implemented methodology is presented in figure 3.7. The research has been conducted through several phases. After retrieving the data from the repository, the dataset has been analyzed using various visualization approaches to gain a detailed understanding of it and then, it has been meticulously pre-processed to transform it into a clean and suitable dataset that can be used for deep learning. A comparative study of several segmentation models and feature prioritizing techniques has also been performed through different performance matrices to evaluate the efficacy of the classifiers.

## 3.4 Chapter Summary

This chapter describes the details of the datasets and the procedure of the data prepossessing, the proposed methodology with a detailed overview of the original architecture, and also the proposed architecture, and implementation details. 3D-UNT is employed to open the image channel with preserving the data of the Z-axis and then InceptionV3 is responsible

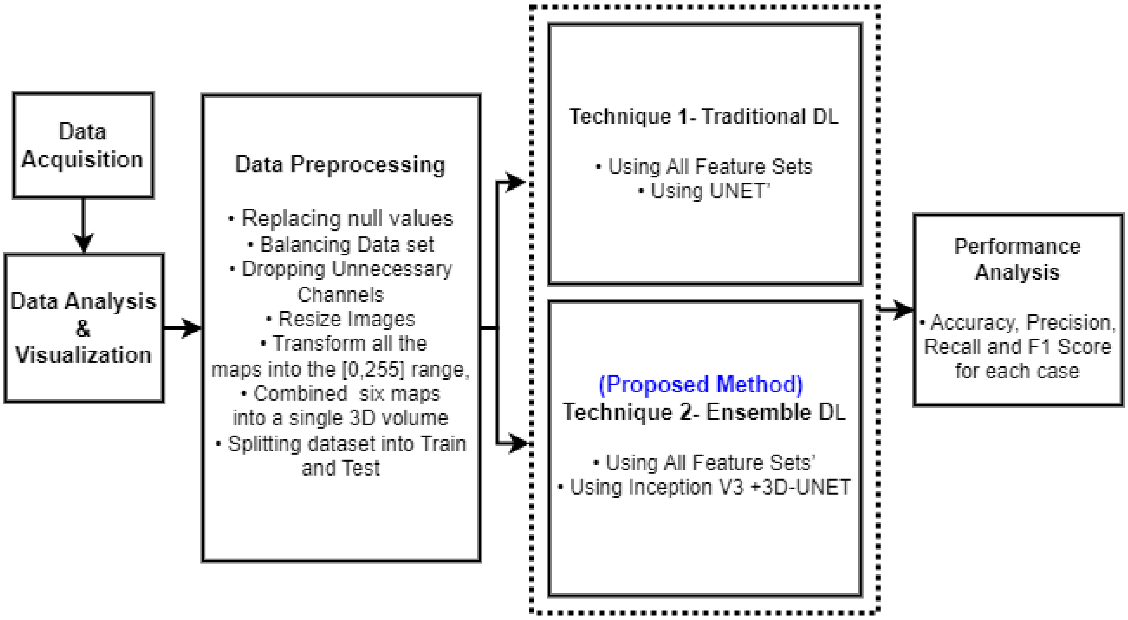


**Fig. 3.7.** Framework of implemented methodology

for extracting the global and local features efficiently. The suggested hybrid method has extracted the most significant feature set from the images and then stacking ensemble deep learning techniques have been employed to segment the images.

# CHAPTER 4

## RESULTS AND ANALYSIS

The chapter discusses the results of the ensemble deep learning method that was proposed and implemented by this thesis using human brain MRI. The results of the proposed methodology are subdivided into parts: Quantitative analysis and qualitative analysis. In Quantitative analysis, this study the numeric results with the other methods. In qualitative analysis, this study used visualization of segmented Ischemia with the actual ground truth. Finally, the result findings have been discussed elaborately.

### 4.1 Quantitative analysis

It previously discussed the specifics of the dataset that was utilized to test and assess the ischemia lesion segmentation scheme suggested. While training, It continuously monitored the validation loss and set up an early stop callback function. The framework was Set up for 185 epochs, and every epoch calculates the Dice co-efficient similarity, Intersection over Union, Precision, and Recall, and on table 4.1, decorate the mean results for all of them. Figures 4.1 also illustrate losses and other similarities visually. In the training period, this method achieves maximum results of 0.80, 0.82, 0.76, and 0.98 in the context of DSC, IoU, Precision, and recall, respectively. On testing, the dataset has 350 labeled subjects that were evaluated in two stages: whole datasets at a time (results in table 4.1) and one by one (results in table 4.2 with standard deviation). In Table 4.2, the segmentation results of this method are compared across different deep-learning architectures. This study specifically examines methods that train their models using the ISLES 2017 dataset. Upon reviewing the results table, it's evident that despite the dataset's small size, the outcomes are notably strong, surpassing those achieved by models trained on the same dataset or even the winners (Mok and Chung, 2017) of the segmentation competition held on this dataset in 2017.

**Table 4.1:** Result summary of the proposed model

| | Training | Validation | Testing |
|---|---|---|---|
| Accuracy | 0.98 | 0.98 | 0.99 |
| IoU | 0.64 | 0.52 | 0.65 |
| DSC | 0.58 | 0.49 | 0.64 |
| Recall | 0.93 | 0.74 | 0.85 |
| Precision | 0.56 | 0.51 | 0.61 |
| Loss | 0.42 | 0.50 | 0.35 |

Indeed, assembling a sizable dataset for brain stroke research, complete with ground truth annotations, can be quite challenging. With a larger dataset, it is reasonable to anticipate that the error rate would ideally decrease, potentially achieving less than 1% percent margin of error.

### 4.2 Qualitative analysis

Figure 4.2 provides a graphical representation of the segmented results produced by the suggested framework. The actual site of the ischemic stroke as determined by the patient's MRI, a prediction from the suggested model, as well as the combination of the classified result and the actual data for each patient are all represented in these pictures as four images in a series. On the fusion comparison image, the white area, red area, and sky blue area represent True-positive, False-negative, and False-positive. In Figure 4.2, performance indicators (dice coefficient, recall, precision) for five sufferers, p3, p8, p18, p19, and p33 are shown to be p3 (0.70, 0.57, 0.90), p8 (0.66, 0.58, 0.77), p18 (0.76, 0.71, 0.81), p19 (0.55, 0.39, 0.96), and p33 (0.72, 0.63, 0.87), respectively. Observe that, occasionally, as suggested by the output of the visual segmentation, the simulation fails to cover the entire segmented actuality.

#### 4.2.1 Comparative analysis utilizing existing methods

The proposed approach has been compared to several widely used methods for segmenting brain imaging data based on the ISLES Challenge 2017 dataset. These architectures were developed using identical datasets but employed different predictive frameworks. Table 4.2 presents all the comparisons, including results from the competition and newly published

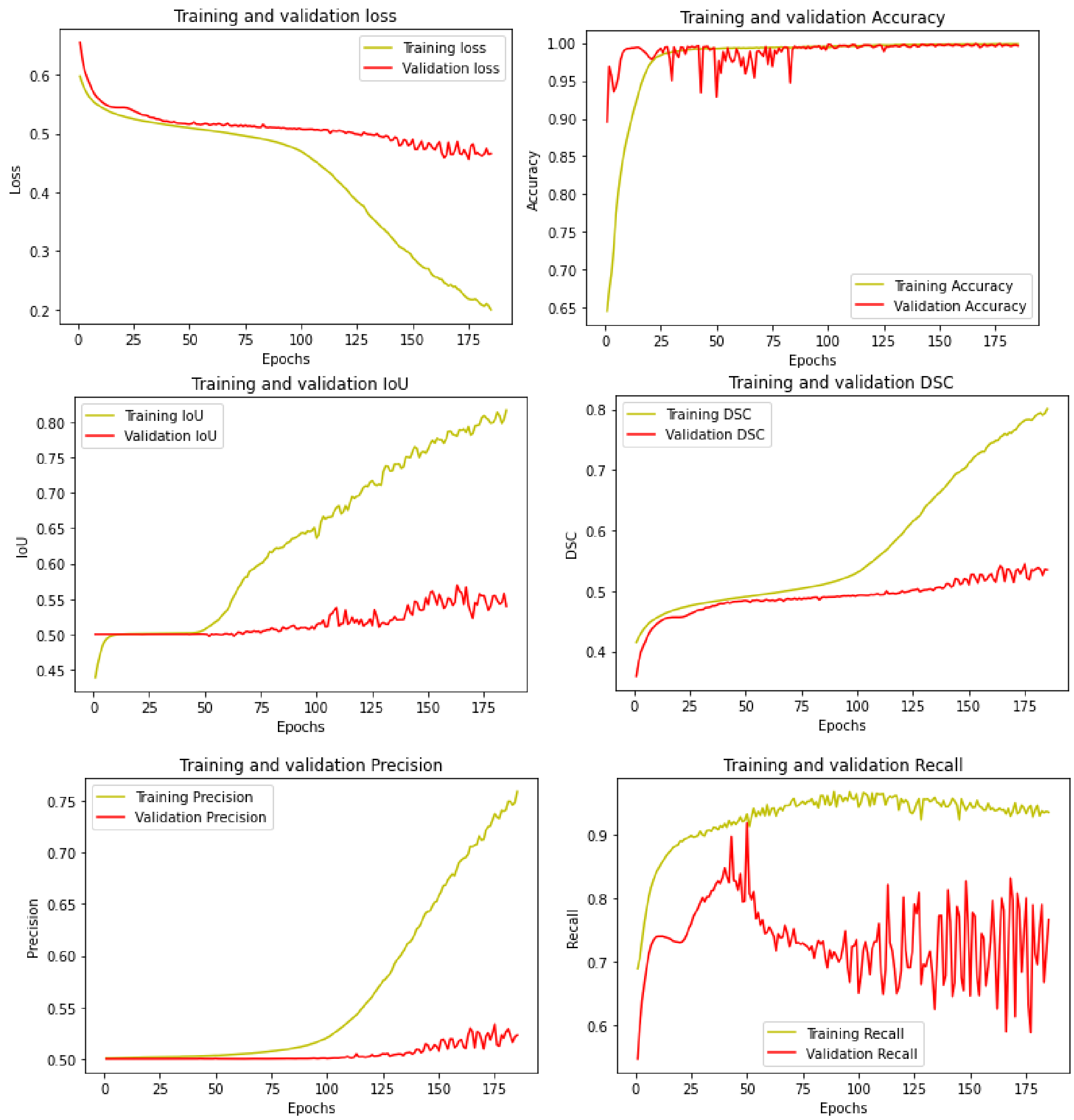


**Fig. 4.1.** Measurement Graphs while training

articles. In the ISLES 2017 competition, the prize-winning team (Choi et al., 2017) accomplished a DSC of 0.31. Following the competition, (Perez Malla et al., 2019) improved learning techniques using CNN, resulting in a 7% increase in mean dice score contrasted with the baseline model. By modifying the U-NET structure, (Pinto et al., 2018) conducted experiments with different pathways, achieving the highest dice score of 0.31 using their two-pathway model. In an attempt to improve the results, combined all the clinical information as a single piece of information and applied 2D U-net for segmentation, but the expected outcome was not satisfactory.

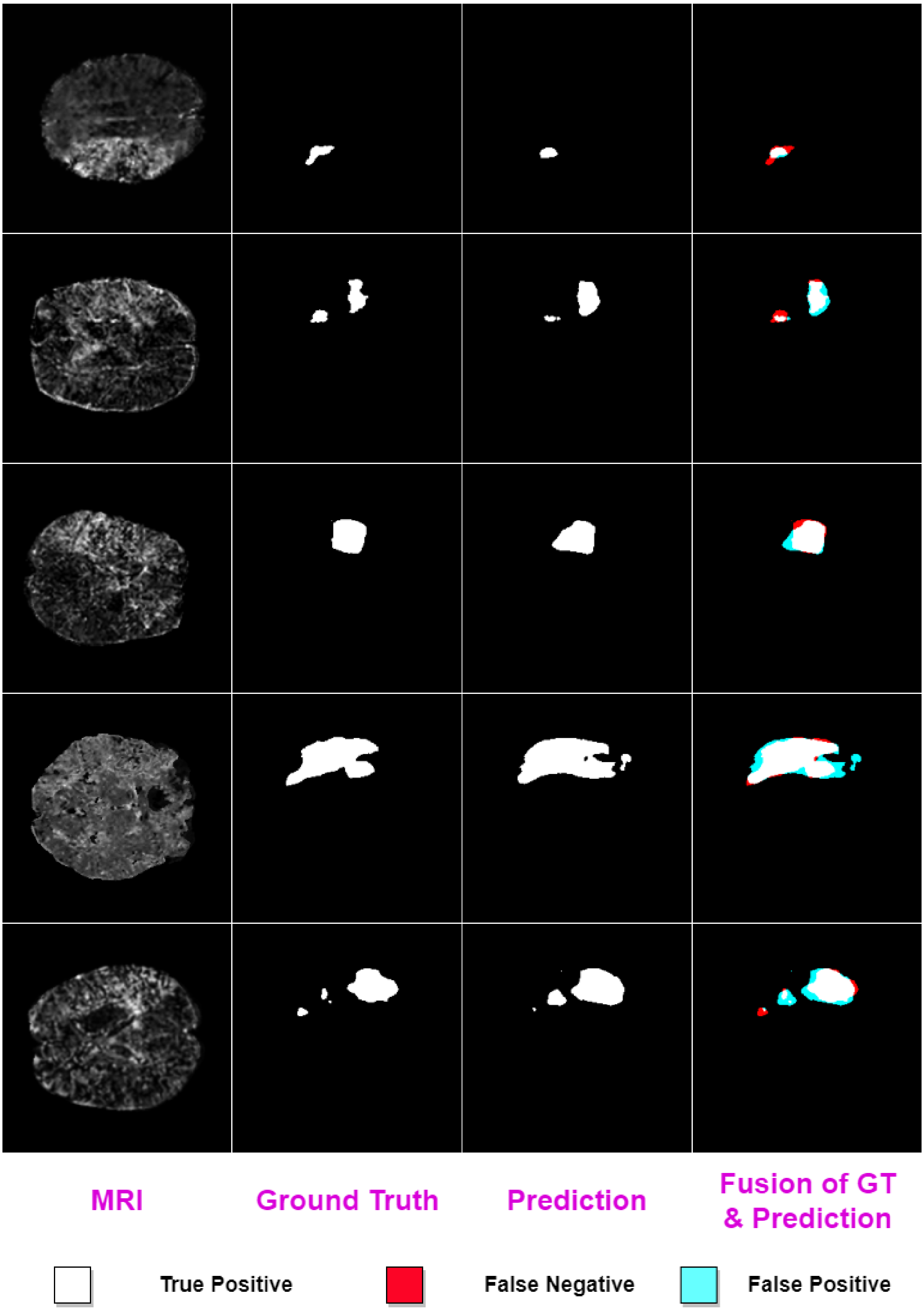


**Fig. 4.2.** Visual comparison between Ground truth and Prediction

Nevertheless, this thesis's suggested architecture improves on earlier studies by making use of the z-axis feature and extracting deep features using Inceptionv3.

**Table 4.2:** Compared between different Methods (Based on ISLES 2017)

| Reference | Dice | Precision | Recall |
|---|---|---|---|
| Mok and Chung (2017) | 0.32 ± 0.23 | 0.34 ± 0.27 | 0.39 ± 0.27 |
| Kwon et al. (2018) | 0.31 ± 0.23 | 0.36 ± 0.27 | 0.45 ± 0.30 |
| Monteiro and Oliveira (2017) | 0.30 ± 0.22 | 0.34 ± 0.27 | 0.51 ± 0.30 |
| Lucas and Heinrich (2017) | 0.29 ± 0.21 | 0.34 ± 0.26 | 0.51 ± 0.32 |
| Pinto et al. (2018) | 0.35 ± 0.22 | 0.26 ± 0.23 | 0.61 ± 0.28 |
| Robben and Suetens (2017) | 0.27 ± 0.22 | 0.44 ± 0.32 | 0.39 ± 0.31 |
| Pisov et al. (2017) | 0.27 ± 0.20 | 0.31 ± 0.27 | 0.39 ± 0.29 |
| Rivera et al. (2017) | 0.19 ± 0.16 | 0.27 ± 0.25 | 0.21 ± 0.17 |
| Islam et al. (2018) | 0.19 ± 0.18 | 0.29 ± 0.28 | 0.25 ± 0.25 |
| This method | 0.43±0.31 | 0.58 ±0.39 | 0.36±0.30 |

## 4.3 Chapter Summary

The ensemble deep learning method's implementation outcomes were covered in this chapter using both quantitative and qualitative analysis. While qualitative analysis depicts the genuine annotated ground truth that explains the true positive, false negative, and false positive quantitative analysis relates to the outcomes obtained throughout the implementation period. Next, the outcomes are contrasted with those of the other models that made use of the ISLES 2017 datasets.

# CHAPTER 5

## CONCLUSIONS

The last notions are covered in this chapter as well as are discussed in many sections. These include future work, constraints, implications, and results of the thesis. The thesis results are presented first in an organized fashion. The consequences of this argument are then spoken about. The thesis's weaknesses are next mentioned, and then there are a few possible directions for future research.

### 5.1 Thesis Outcomes

Several findings have been found from this research work, which can be very helpful in the domain of automated Ischemic stroke segmentation.

- The SLR summarizes the existing relevant studies concentrating on the use of various computer-assisted methodologies for Ischemic detection by thoroughly examining them to explore the state-of-art viewpoints, identify the shortcomings, and determine the possible future study areas.
- An extended machine learning method has been developed to segment the Ischemic stroke area based on the image data in this study as such the first research objective has been fulfilled.
- To acquire the final research objective, the comparative performance analysis of both kinds of proposed techniques with the previously adopted ML techniques highlights the efficacy of the suggested methodologies in this domain for Ischemic stroke segmentation.
- It is also mentioned the challenges that have to be faced in ischemic stroke detection.

In the field of medical image processing, recent breakthroughs in deep learning have demonstrated promising results. This study explored a variety of stroke-related issues from a state-of-the-art perspective. This thesis recognizes that comparing studies is challenging because they use different performance measurements for different tasks, as well as different datasets, methodologies, and tuning parameters.

## 5.2 Implications

The strategy used in this work to segment patient MRI data is based on stacking ensemble segmentation, which is a novel approach in this field. It aggregates classical and boosting or bagging ensemble models to provide a more robust prediction. The practical implementation of deep learning in important real-life situations is still not widely acknowledged, despite recent advances showing promising outcomes in healthcare image processing. The main reasons for this reluctance are worries about their efficacy, consistency, and accuracy when working with different real-world medical diagnostic data. An automated technique for dividing up acute stroke lesions using MRI data is presented in this thesis. To improve segmentation performance, This thesis used a unique method that blends Inceptionv3 with 3D U-Net approaches. This technique makes use of Inception's modules with various kernel sizes to extract features effectively. This method works well for addressing the issues of overfitting and the vanishing gradient problem. The resulting predictions can inform treatment choices in a clinical context. The intentions involve examining the architecture's learning patterns and doing an interpretability evaluation based on information perfusion maps to guarantee the correctness of the predictions made about the data driving lesion results.

The study's findings can significantly aid doctors in their difficult patient evaluation process by demystifying the intricate diagnostic process for ischemic stroke. This computer method can be used in remote healthcare institutions where resources and skilled doctors are limited to independently identify epidemics. Furthermore, the literature review carried out here will help academics and medical professionals discuss the value of various computer-assisted methods, including image processing and machine learning, in real-time decision-making for early illness diagnosis.

## 5.3 Thesis Limitations

The research has a few limitations as well which are stated below:

- The primary issue of this study was to gather a dataset because the research relies on the clinical data of the patients. Because it is very difficult to obtain medical data or patient images in the least developed countries, machine learning techniques have only been used for a small number of images because there is a lack of a dataset.

- The dataset that has been used to implement the proposed methodology is open access data, the researchers of this thesis could not directly obtain real-time data from any hospital due to some obstacles.

- One of the study's shortcomings was that it only used machine learning algorithms to a limited amount of patient symptom data due to a lack of a large dataset.

- As the work is related to healthcare analytics, it is important to conduct a systematic evaluation of the proposed technique in the context of the doctor's perspective. However, in the case of this research work, this kind of evaluation has not been conducted.

- The suggested method relies on a stacked ensemble machine learning classifier and deep learning feature extraction, which might be challenging to understand and make the technology appear mysterious to doctors.

- The proposed technique can only be used by patients and doctors if it has been implemented as an interactive platform. However, no interactive software version has been designed or developed based on the proposed technique for practical use.

## 5.4 Future Work

There are many ways to enhance this research work in the future. These are discussed as follows:

- This study can be incorporated with a real-time dataset from a hospital in Bangladesh and then apply the proposed techniques for Ischemic stroke segmentation.

- The research work can be elaborated through the development of an interactive mobile application or website so that the patients or doctors can use the prediction of Ischemic stroke practically.

- The results of the proposed predictive models can be evaluated more critically in the context of the doctor's perspective to analyze its efficacy clinically.

- Explainable AI is crucial for providing enough rationale for AI system predictions in intelligent healthcare applications. As a result, the present study's eXplainable AI (XAI) methodologies may be used to further expand the Ischemia diagnosis procedure.

- The suggested technique is also applicable to other domains of anal clinical disease prediction in healthcare.

# REFERENCES


Alhelal, D., Younis, A. K., & Al-Mallah, R. H. A. (2021). Detection of brain stroke in the MRI image using FPGA. *TELKOMNIKA (Telecommunication Computing Electronics and Control)*, *19*(4), 1307–1315.

Bendiabdallah, M. H., & Settouti, N. (2021). A comparison of U-Net backbone architectures for the automatic white blood cells segmentation. *WAS Science Nature (WASSN) ISSN: 2766-7715*, *4*(1).

Castillo, D., Lakshminarayanan, V., & Rodríguez-Álvarez, M. J. (2021). MR images, Brain lesions, and Deep learning. *Applied Sciences*, *11*(4), 1675.

Chen, L.-C., Papandreou, G., Kokkinos, I., Murphy, K., & Yuille, A. L. (2017). Deeplab: Semantic image segmentation with deep convolutional nets, atrous convolution, and fully connected CRFS. *IEEE transactions on pattern analysis and machine intelligence*, *40*(4), 834–848.

Chen, Q., Xu, J., & Koltun, V. (2017). Fast image processing with fully-convolutional networks. *Proceedings of the IEEE International Conference on Computer Vision*, 2497–2506.

Chin, C.-L., Lin, B.-J., Wu, G.-R., Weng, T.-C., Yang, C.-S., Su, R.-C., & Pan, Y.-J. (2017). An automated early ischemic stroke detection system using CNN deep learning algorithm. *2017 IEEE 8th International conference on awareness science and technology (iCAST)*, 368–372.

Choi, Y., Kwon, Y., Paik, M. C., & Joon, B. (2017). Ischemic stroke lesion segmentation with convolutional neural networks for small data. *ISLES 2017 Challenge*.

Çiçek, Ö., Abdulkadir, A., Lienkamp, S. S., Brox, T., & Ronneberger, O. (2016). 3d U-Net: Learning dense volumetric segmentation from sparse annotation. *Medical Image Computing and Computer-Assisted Intervention–MICCAI 2016: 19th International Conference, Athens, Greece, October 17-21, 2016, Proceedings, Part II 19*, 424–432.

Do, L.-N., Baek, B. H., Kim, S. K., Yang, H.-J., Park, I., & Yoon, W. (2020). Automatic assessment of aspects using Diffusion-Weighted Imaging in acute Ischemic Stroke using Recurrent Residual Convolutional neural network. *Diagnostics*, *10*(10), 803.

Gaidhani, B. R., Rajamenakshi, R., & Sonavane, S. (2019). Brain stroke detection using convolutional neural network and deep learning models. *2019 2nd International conference on intelligent communication and computational techniques (ICCT)*, 242–249.

Gautam, A., & Raman, B. (2020). Local gradient of gradient pattern: A robust image descriptor for the classification of brain strokes from computed tomography images. *Pattern Analysis and Applications*, *23*(2), 797–817.

He, K., Gkioxari, G., Dollár, P., & Girshick, R. (2017). Mask R-CNN. *Proceedings of the IEEE international conference on computer vision*, 2961–2969.

He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep Residual learning for Image Recognition. *Proceedings of the IEEE conference on computer vision and pattern recognition*, 770–778.

Hu, X., Luo, W., Hu, J., Guo, S., Huang, W., Scott, M. R., Wiest, R., Dahlweid, M., & Reyes, M. (2020). Brain Segnet: 3D local Refinement network for brain lesion segmentation. *BMC medical imaging*, *20*(1), 1–10.

ISLES Challenge. (2017). *ISLES 2017 Challenge: Ischemic Stroke Lesion Segmentation*. Retrieved July 11, 2022, from https://www.isles-challenge.org/ISLES2017/

Jeena, R., & Kumar, S. (2013). A comparative analysis of MRI and CT brain images for stroke diagnosis. *2013 annual international conference on emerging research areas and 2013 international conference on microelectronics, communications and renewable energy*, 1–5.

Kamnitsas, K., Ledig, C., Newcombe, V. F., Simpson, J. P., Kane, A. D., Menon, D. K., Rueckert, D., & Glocker, B. (2017). Efficient multi-scale 3D CNN with fully connected CRF for accurate brain lesion segmentation. *Medical image analysis*, *36*, 61–78.

Karthik, R., Menaka, R., Hariharan, M., & Won, D. (2021). Ischemic lesion segmentation using ensemble of Multi-scale region aligned CNN. *Computer Methods and Programs in Biomedicine*, *200*, 105831.

Karthik, R., Menaka, R., Johnson, A., & Anand, S. (2020). Neuroimaging and deep learning for brain stroke detection-a review of recent advancements and future prospects. *Computer Methods and Programs in Biomedicine*, *197*, 105728.

Kleesiek, J., Urban, G., Hubert, A., Schwarz, D., Maier-Hein, K., Bendszus, M., & Biller, A. (2016). Deep MRI brain extraction: A 3D convolutional neural network for skull stripping. *NeuroImage*, *129*, 460–469.

Kumar, A., Upadhyay, N., Ghosal, P., Chowdhury, T., Das, D., Mukherjee, A., & Nandi, D. (2020). CSNET: A new DeepNet framework for ischemic stroke lesion segmentation. *Computer Methods and Programs in Biomedicine*, *193*, 105524.

Lin, C., Li, L., Luo, W., Wang, K. C., & Guo, J. (2019). Transfer learning based traffic sign recognition using Inception-V3 model. *Periodica Polytechnica Transportation Engineering*, *47*(3), 242–250.

Liu, C.-F., Hsu, J., Xu, X., Ramachandran, S., Wang, V., Miller, M. I., Hillis, A. E., & Faria, A. V. (2021). Deep learning-based detection and segmentation of diffusion abnormalities in acute ischemic stroke. *Communications Medicine*, *1*(1), 1–18.

Liu, L., Chen, S., Zhang, F., Wu, F.-X., Pan, Y., & Wang, J. (2020). Deep Convolutional Neural Network for automatically segmenting acute ischemic stroke lesion in multi- modality MRI. *Neural Computing and Applications*, *32*(11), 6545–6558.

Liu, L., Kurgan, L., Wu, F.-X., & Wang, J. (2020). Attention convolutional neural network for accurate segmentation and quantification of lesions in ischemic stroke disease. *Medical Image Analysis*, *65*, 101791.

Lucas, C., & Heinrich, M. P. (2017). 2D multi-scale res-net for stroke segmentation. *ISLES 2017 Challenge*.

Mok, T., & Chung, A. (2017). Deep adversarial networks for stroke lesion segmentation. *Ischemic Stroke Lesion Segmentation–ISLES challenge 2017, held in conjunction with MICCAI 2017, Quebec, Canada*.

Monteiro, M., & Oliveira, A. L. (2017). Fully convolutional neural network for 3D stroke lesion segmentation. *Ischemic Stroke Lesion Segmentation–ISLES challenge 2017, held in conjunction with MICCAI 2017, Quebec, Canada*.

Nishio, M., Koyasu, S., Noguchi, S., Kiguchi, T., Nakatsu, K., Akasaka, T., Yamada, H., & Itoh, K. (2020). Automatic detection of acute ischemic stroke using non-contrast Computed Tomography and two-stage deep learning model. *Computer Methods and Programs in Biomedicine*, *196*, 105711.

Pan, J., Wu, G., Yu, J., Geng, D., Zhang, J., & Wang, Y. (2021). Detecting the early infarct core on non-contrast CT images with a Deep Learning Residual Network. *Journal of Stroke and Cerebrovascular Diseases*, *30*(6), 105752.

Perez Malla, C. U., Valdes Hernandez, M. d. C., Rachmadi, M. F., & Komura, T. (2019). Evaluation of enhanced learning techniques for segmenting ischaemic stroke lesions in brain Magnetic Resonance Perfusion Images using a convolutional neural network scheme. *Frontiers in Neuroinformatics*, *13*, 33.

Pinto, A., Mckinley, R., Alves, V., Wiest, R., Silva, C. A., & Reyes, M. (2018). Stroke lesion outcome prediction based on MRI imaging combined with clinical information. *Frontiers in neurology*, *9*, 1060.

Pisov, M., Belyaev, M., & Krivov, E. (2017). Neural networks ensembles for ischemic stroke lesion segmentation.

Robben, D., & Suetens, P. (2017). Dual-scale fully convolutional neural network for final infarct prediction. In *Ischemic stroke lesion segmentation-isles challenge 2017, held in conjunction with miccai 2017, date: 2017/09/10-2017/09/10, location: Quebec city, quebec, canada*.

Ronneberger, O., Fischer, P., & Brox, T. (2015). U-Net: Convolutional networks for Biomedical image segmentation. *Medical Image Computing and Computer-Assisted Intervention– MICCAI 2015: 18th International Conference, Munich, Germany, October 5-9, 2015, Proceedings, Part III 18*, 234–241.

Selçuk, A. A. (2019). A Guide for Systematic Reviews: Prisma. *Turkish archives of otorhinolaryngology*, *57*(1), 57.

Shinohara, Y., Takahashi, N., Lee, Y., Ohmura, T., & Kinoshita, T. (2020). Development of a deep learning model to identify hyperdense MCA sign in patients with acute ischemic stroke. *Japanese Journal of Radiology*, *38*(2), 112–117.

Sovetkin, E., Achterberg, E. J., Weber, T., & Pieters, B. E. (2020). Encoder–Decoder seman- tic segmentation models for electroluminescence images of thin-film photovoltaic modules. *IEEE Journal of Photovoltaics*, *11*(2), 444–452.

Stier, N., Vincent, N., Liebeskind, D., & Scalzo, F. (2015). Deep learning of tissue fate features in acute ischemic stroke. *2015 IEEE international conference on bioinformatics and biomedicine (BIBM)*, 1316–1321.

Szegedy, C., Ioffe, S., Vanhoucke, V., & Alemi, A. (2017). Inception-v4, Inception-Resnet and the impact of residual connections on learning. *Proceedings of the AAAI con- ference on artificial intelligence*, *31*(1).

Szegedy, C., Vanhoucke, V., Ioffe, S., Shlens, J., & Wojna, Z. (2016). Rethinking the Inception architecture for computer vision. *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2818–2826.

Szegedy, C., Liu, W., Jia, Y., Sermanet, P., Reed, S., Anguelov, D., Erhan, D., Vanhoucke, V., & Rabinovich, A. (2015). Going deeper with convolutions. *Proceedings of the IEEE conference on computer vision and pattern recognition*, 1–9.

Tandon, A., Dhir, A., Islam, A. N., & Mäntymäki, M. (2020). Blockchain in healthcare: A systematic literature review, synthesizing framework and future research agenda. *Computers in Industry*, *122*, 103290.

Wu, G., Chen, X., Lin, J., Wang, Y., & Yu, J. (2021). Identification of invisible ischemic stroke in noncontrast CT based on novel two-stage convolutional neural network model. *Medical Physics*, *48*(3), 1262–1275.

Xie, S., & Tu, Z. (2015). Holistically-nested edge detection. *Proceedings of the IEEE international conference on computer vision*, 1395–1403.

Yu, Y., Xie, Y., Thamm, T., Gong, E., Ouyang, J., Huang, C., Christensen, S., Marks, M. P., Lansberg, M. G., Albers, G. W., et al. (2020). Use of deep learning to predict final ischemic stroke lesions from initial magnetic resonance imaging. *JAMA network open*, *3*(3), e200772–e200772.

Zhang, R., Zhao, L., Lou, W., Abrigo, J. M., Mok, V. C., Chu, W. C., Wang, D., & Shi, L. (2018). Automatic segmentation of acute ischemic stroke from DWI using 3-D fully convolutional Densenets. *IEEE transactions on medical imaging*, *37*(9), 2149–2160.

Zhang, Y., Liu, S., Li, C., & Wang, J. (2021). Application of deep learning method on ischemic stroke lesion segmentation. *Journal of Shanghai Jiaotong University (Science)*, 1–13.

Zhao, B., Liu, Z., Liu, G., Cao, C., Jin, S., Wu, H., & Ding, S. (2021). Deep learning-based acute ischemic stroke lesion segmentation method on multimodal MR images using a few fully labeled subjects. *Computational and Mathematical Methods in Medicine*, *2021*.

Zhao, H., Shi, J., Qi, X., Wang, X., & Jia, J. (2017). Pyramid scene parsing network. *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2881–2890.