DEEP LEARNING MODELS TO DIAGNOSE BRAIN STROKE

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This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

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APPROVAL

This Project titled **"Deep Learning Models To Diagnose Brain Stroke"**, submitted by Asif Mahmud, ID No:183-15-2315, Raisul Islam, ID No:183-15-2319 to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 06/02/2023.

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ABSTRACT

Brain Hemorrhage has gotten to be an extreme issue in the world. Brain Hemorrhage is also called 'Brain Stroke' in our country. The amount of the stroke may be a particularly difficult process among all of them; the brain stroke is the toughest one. There are three types of strokes. Hemorrhagic Stroke, Ischemic Stroke and Transient Ischemic Attack (TIA).One of the discrete methods that emerged as a first-line, radiation-free method of diagnosing brain stroke is magnetic resonance imaging (MRI). Most of the people (87%) are affected by Ischemic stroke. To distinguish this hemorrhage, we got to do a lab test at therapeutic. But that's exceptionally costly for our country. So, we choose to do something for them. After research, we developed a project which can detect this type of hemorrhage using deep learning neural network based algorithm. When it comes to picture identification, deep learning has made significant progress. To do that we collected raw data (CT Scan Copy) from a number of hospital, we preprocessed it with a help of radiologist and finally trained our model to nail our goal which is detecting hemorrhage stroke. Right now, we have been found that VGG-16 achieves a high rate of accuracy with a minimal level of complexity. It's about 93 up percentage accuracy in total.Keywords: Brain Stoke, MRI, VGG-16.

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CHAPTER 1

Introduction

1.1 Introduction

One of the most widely studied topics today is brain stroke. Strokes are defined by the World Health Organization which is an acute, focal or diffuse, dysfunction of the brain, originating for vessels and lasting for a period longer than a day. The brain, which has billions of cells, is one of the body's essential organs. Stroke is the third leading disease of death in the United States. There are 15 million people suffer stroke worldwide every year (World Health Organization). A high-grade stroke is also referred to as malignant. Cancerous strokes are not benign strokes. As a result, it doesn't spread to other brain regions. The cancerous stroke, however, is a malignant stroke. Because of this, it easily and quicklyspreads to other parts of the body with arbitrary boundaries, making it dangerous. It results in instant death, according to medical specialists. Clinical professionals must help patients access more effective e-health care systems because it results in immediatemortality. Health care systems are useful in a variety of medical fields. Biomedical imaging technologies based on computer vision are becoming more important as they give radiologists recognition data for solving treatment-related issues more effectively. There are numerous medical imaging techniques and approaches, including X-rays, MRIs, ultrasounds, and computerized tomography (CT), which have a significant impact on how patients are diagnosed and treated. In particular, an MRI image can be used to track a stroke's progression using modeling. MRI images contain more data thanCT or ultrasound images do. A magnetic resonance imaging (MRI) image may be usedto detect irregularities in brain tissue and offer detailed information on brain anatomy.It affects a lot of individuals right now, and therapy is pricey. People sometimes want to avoid having a stroke because of the high cost of treatment, but a stroke can be fatal. We are concerned about the rising number of stroke cases in Bangladesh and around the world. There is a lot of research being done on brain stroke right now. Patients will find it simpler to diagnose strokes thanks to our software, and doctors will find it simpler to keep track of their patients. In order for our software to understand brain stroke, we used a lot of images of the brain for brain stroke as well as a lot of photographs of what causes a brain stroke. We believe that people will get far more from our project.

1.2 Motivation

- We dream to bring wrong treatment into Level Zero
- We want to reduce pressure from the patient
- We want to see the effects of our innovation throughout the world.
- We want to gift the underworld a better healthy life

Stroke with intracerebral hemorrhage (ICH) is the most fatal and incapacitating type. Hemorrhagic strokes, which are brought on by an immediate hemorrhage, account for 15% of acute strokes. Intracerebral hemorrhage (ICH) and subarachnoid hemorrhage, which account for around 5% of all strokes, are the two main kinds of hemorrhagic strokes. This page deals with intracranial hemorrhage (ICH), a potentially fatal form of stroke that robs the brain of oxygen and blood flow.

1.3 Rationale of the Study

This section reviews literature on brain stroke related work in computer science after outlining research linked to addressing brain stroke.

Stroke happens when blood vessels in the brain burst and when the brain's blood supply is cut off. Every year, 15 million people experience a stroke. In Europe, there are 650,000 stroke fatalities annually. In Bangladesh, a stroke is the third most common cause. The World Health Organization ranks Bangladesh as having the 84th highest number of brain stroke-related fatalities worldwide. Several recent research endeavors have concentrated their emphasis on Brain Stroke issues in an effort to lessen the detrimental effects of brain stroke globally. One of these is BCI (Brain-Computer Interface in Stroke Rehabilitation), a computer-based system that converts brain impulses into commands for an output device to carry out a desired action in the case of stroke.

Another project involves using angiography, MRI, and CT scans to diagnose strokes. Stroke prevention and treatment methods for brain attack. Alteplase is currently the go-to treatment for ischemic stroke, and computer technology and virtual reality help with brain rehabilitation. Using new software, it is possible to determine the sort of brain damage and the likelihood of recovery and recommend the most effective ways to observe the patient.

1.4 Research Questions

- What is the Brain Stroke status globally?
- What are the associated factors with brain Stroke?
- Which algorithm perform well and why?
- What is image processing?
- How does CNN, VGG-16 work?

1.5 Research Objective

- To find out the Brain Stroke status.
- To identify the associated factors.
- Finding the best performing algorithm.
- Making awareness to reduce the percentage of brain stroke in every year.
- Giving message with the effect of lacking knowledge on brain stroke causes to peoples.
- To increase the knowledge on brain stroke preventing factors.

1.6 Report Layout

This research paper's contents are:

I. In the first chapter we discuss about the motivation, rational study and objectives.

II. In the second chapter we discus about the related work and research summary.

III. Research methodology, data collection and preparation, Research Subject and Instrumentation and discuss about the applied model in the Chapter 3.

IV. The experimental evaluation and numerical result of the study are discussed in Chapter 4.

V. The fifth chapter offer the summary, conclusion and future work.

CHAPTER 2

Background Study

2.1 Comparative Analysis

Brain stroke is a dangerous and acute cerebrovascular illness that is a significant cause of mortality. It can be hemorrhagic, caused by blood flowing into brain tissue through a burst intracranial arterial, or ischemic, caused by vascular blockage in the brain due to a blood clot (thrombosis). Visible symptoms are identical in both situations, making differentiation exceedingly difficult without modern imaging methods. Since human neural tissue is rapidly destroyed as ischemic stroke advances, thrombolytic (or clot-dissolving) medicines can be used to treat ischemic stroke during the first few hours. Contrarily, thrombolytics can be hazardous or even deadly to individuals who are experiencing hemorrhagic stroke, making it crucial to distinguish between the two. In order to expedite clinical choices on therapies and to accelerate the recovery of patients suffering from acute stroke, a quick and accurate diagnosis is essential for patient triage.

Table: 2.1.1 Comparative Analysis

Paper Name	Working Idea	What's new?
Ischemic Stroke detection using Image processing and ANN	Ischemic stroke detection using MRI image, with a six-phase algorithm along with neural networking being applied at the ending phase.	Hemorrhagic stroke detection using a training data set and a test data set to make the system learn and then predict the result.
Detection of Brain Stroke from CT Scan Image	Detection of different types of brain strokes by analyzing CT scan images manually, with no machine learning.	Including machine learning along with image processing for system learning and better prediction.
Medical image analysis methods in MR/CT-imaged acute-subacute ischemic stroke lesion: Segmentation, prediction and insights	Using image analysis method of 2D/3D images along with mathematical model for detecting ischemic stroke.	Precise training process to detect hemorrhagic stroke with the help of neural networking.

into dynamic evolution simulation models. A critical appraisal		
Ischemic Stroke Detection System with a Computer-Aided Diagnostic Ability Using an Unsupervised Feature Perception Enhancement Method	Ischemic stroke detection system with a computer-aided diagnostic ability using a four-step unsupervised feature perception enhancement method.	No manual enhancement method introduced

2.2 Research Summary

There is a wealth of knowledge available in the healthcare sector. With the right use of dependable data mining categorization methodology, early disease prediction is achievable. The fields of medicine can benefit from machine learning and data mining. The majority of it is executed properly. The study examines a set of risk factors that are monitored by systems that look out for brain strokes. The suggested method for identifying, classifying, and segmenting brain strokes seems to be quite accurate and effective [16]. To reach this level of precision, automatic or somewhat automatic processes were necessary. The research claims that segmentation and classification can be carried out automatically utilizing a technique that utilizes CNN and operates in compact 3x3 kernels.

CNN is a machine learning method that use neural networks with layers for result classification. Feature extraction, segmentation, average filtering, preprocessing, CNN, and VGG-16 were some of the processes used in these at various stages. Through categorization and identification using data mining techniques, significant links and patterns in the data can be found. Segmentation, classification, identification, data collection, pre-processing, and average filtering are used in this data mining and feature extraction for CNN. The approach utilized in this study is pre-processing, which eliminates noisy data from the data received during data collecting. Following is the average filtering. After that, pixels-based detection is performed using the segmentation technique. Then, many features including PSNR, MEAN, ENTROPY, SD, etc., were retrieved. T1 and FLAIR are the MRI imaging techniques used by CNN. They also employ Multi FD to extract the tissue-texture of brain strokes. For greater performance, they employ support vector machines and neural networks. segmentation, classification, identification, data gathering, pre-processing, and average filtering for feature extraction in CNN. The technique utilized in this study is pre-processing, which eliminates noisy data from the data received during data collecting. Following is the average filtering. After that, pixels-based detection is performed using the segmentation technique. Then, many features including PSNR, MEAN, ENTROPY, SD, etc., were retrieved. T1 and FLAIR are the MRI imaging techniques used by CNN. They also employ Multi FD to extract the tissue-texture of brain strokes. For greater performance, they employ support vector machines and neural networks.

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In AI, they also employ the Anaconda framework. TensorFlow, too. They also experiment with multi-model brain stroke segmentation, which combines a variety of segmentation algorithms to achieve high efficiency. But it is quite difficult. They understand that data clustering, approximation, pattern matching, optimization methods, and classification approaches all benefit greatly from neural networks. They exclaim that there are three different types of neural networks. These networks are feed-forward, recurrent, and feedback. The feed forward neural network has a single layer and a multilayer architecture. In a single layer network, the hidden layer is not visible. However, it simply has input and output layers. There are a total of three layers in the multilayer. These are the output layer, hidden layer, and input layer. The CNN-based brain stroke classification system divides the technique into two phases: training and testing. Pre-processing, feature extraction, and classification using the Loss function are carried out during the training phase in order to develop a classification model. The author of this article studies, reviews, and describes the methods used to detect brain strokes using MRI and artificial neural networks (ANN). After gathering the MRI image data, the Computer Aided Detection System (CAD) processed it in a number of ways. The initial stage of processing MRI images involved pre- and post-processing to improve and prepare them for analysis. In the second stage, the MRI images were segmented using a threshold utilizing the mean gray level technique. In the second stage, when features are extracted from images using statistical feature analysis, the Particles based on the dependency matrix for the spatial gray levels (SGLD) were selected as the most important characteristic to determine stroke localization. This classification is used to classify both abnormal and typical MR images of various types of brain strokes. Using this differential deep-CNN for image analysis of a pixel-directed pattern with contrast computations has a benefit. A dataset of 25,000 brain MRI scans, both abnormal and normal, was used. Their proposed design generates the best accurate feature map to differentiate between LG and HG gliomas in comparison to the 2D CNN version. Their Deep- CNN offers high-speed and precise detection and classification skills when compared. Convolutional layers, pooling layers, and fully convolutional layers are the three main building blocks of a CNN.

CHAPTER 3

Research Methodology

3.1 Introduction

In the field of cancer research, deep learning (DL) algorithms for deciphering magnetic resonance imaging (MRI) pictures and forecasting brain strokes have advanced quickly. We found that DL models' high accuracy, interpretability, and explanation varied significantly. As a result, we describe a convolutional neural network-based explanation-driven deep learning model.

3.2 Data Collection Procedure

Kaggle has provided data. Kaggle is the location where data scientists spend their evenings and weekends. It is a crowdsourced platform that recruits, teaches, trains, and evaluates a number of data scientists around the world to handle issues utilizing predictive analytics, machine learning, and data science. It has roughly 536,000 active members, and each month it receives about 150,000 entries. began in Melbourne, Australia. When Kaggle first came in Silicon Valley in 2011, investors Max Levchin, PayPal, Index, Hal Varian, Google's Chief Economist, and Khosla Ventures helped the company raise roughly $11 million. In the end, Google bought Kaggle in March 2017. On Kaggle, data science enthusiasts from all around the world compete for prizes and rankings advancement. There are currently only 94 Kaggle Grandmasters [20] left. In every area of employment, data always comes first in order to produce any kind of output. We required the datasets to finish this deep learning process, so we downloaded them from the Kaggle website. Finding the most appropriate datasets for our needs was the biggest challenge using Kaggle, a massive data warehouse. Therefore, we carefully examined the website and other reference documents that we had read for our study summary. We also investigated the UCI machine learning repository, which has one of the largest datasets and a paper warehouse. However, UCI was unable to help us with the datasets, and we unsuccessfully sent more resources from the articles we had found to Kaggle Data Warehouse before they were able to help us find the datasets.

3.3 Data preparation

One of our study project's most difficult tasks is data collection. But the main challengewas to applied the algorithm. As we are not using framework, we have used the raw python coding to do that the data must need to prepare and specified folder to access the datasets. There are numerous numbers of cluster datasets which we have cleaned and integrate for our purpose at last the datasets was ready to apply the algorithms.

3.4 Research Subject and Instrumentation

More sophisticated and complex instruments are required due to the dramatically larger amount of data generated by technology breakthroughs. There is a constant need for new approaches and tools that can assist in turning massive data into useful information and knowledge, even while advancements in Deep Learning technologies have made large data collecting much more prudently necessary. The idea and methods uphold the tradition of giving users access to the theory and practice of finding hidden patterns in huge data sets through knowledge and application. In this study, we use the CNN model, the VGG-16 model, and Python 3.5 to investigate the topic of " Disease Diagnosis by X-ray or CT-scan Using Deep Learning Models".

3.5 Used Deep Learning Models:

To classify brain strokes, we used two different deep learning models. Convolutional Neural Network (CNN) and Visual Geometry Group-16 are two examples (VGG-16). Here is a quick explanation of those.

a) Convolutional Neural Network (CNN):

Convolutional neural networks, often known as CNNs, are a deep learning method that are extensively employed for the classification and recognition of objects and images [21]. Deep Learning uses a CNN to identify things in a picture as a result. Compared to several other classification models, ConvNet requires a lot less pre-processing. Simple sorting methods are still effective, but with enough training, they can learn about new features like ConvNet [22]. The usage of CNNs is widespread in a variety of tasks and applications, such as voice recognition in natural language processing, motion detection, image analysis problems, computer vision, and auto vehicle sensing system.

Because of its significant contribution to all of these quickly evolving and increasing disciplines, CNNs are widely utilized for deep learning.

Let's first talk about the fundamentals, such as what an image is and how it is shown, before we examine how CNN functions. A grayscale image and an RGB picture both have a single plane, but an RGB image is nothing more than a matrix of pixel values. See this picture.

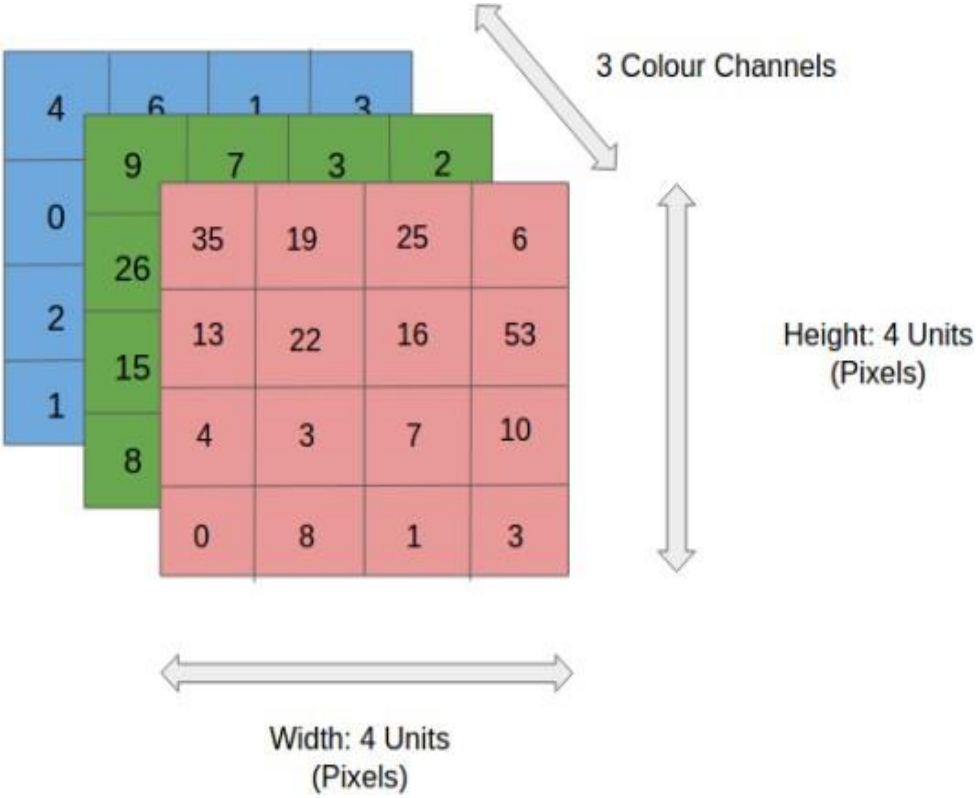

Figure 3.5.1: CNN RGB Image

Figure 3.5.1. Illustrates the preceding discussion that any color image contains three channels: red, green, and blue. An image can exist in a variety of color spaces, including grayscale, CMYK, and HSV. To keep things simple, let's only use grayscale images to show how CNNs operate.

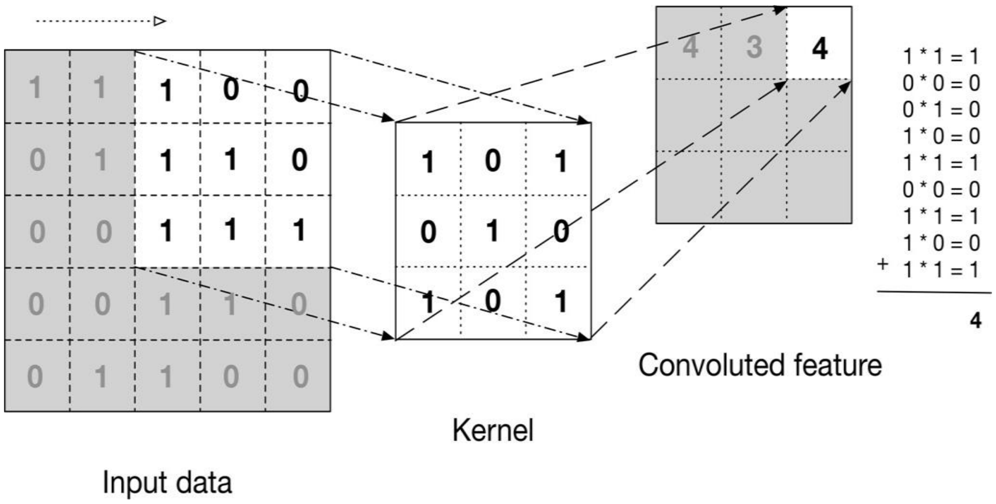

Figure 3.5.2: CNN work procedure

Figure 3.5.2. There is a convolution, as shown in the graphic above. A filter or kernel (3x3 matrix) is applied to the input picture to produce the convolved feature. This convolved function is being passed across to the layer following table.

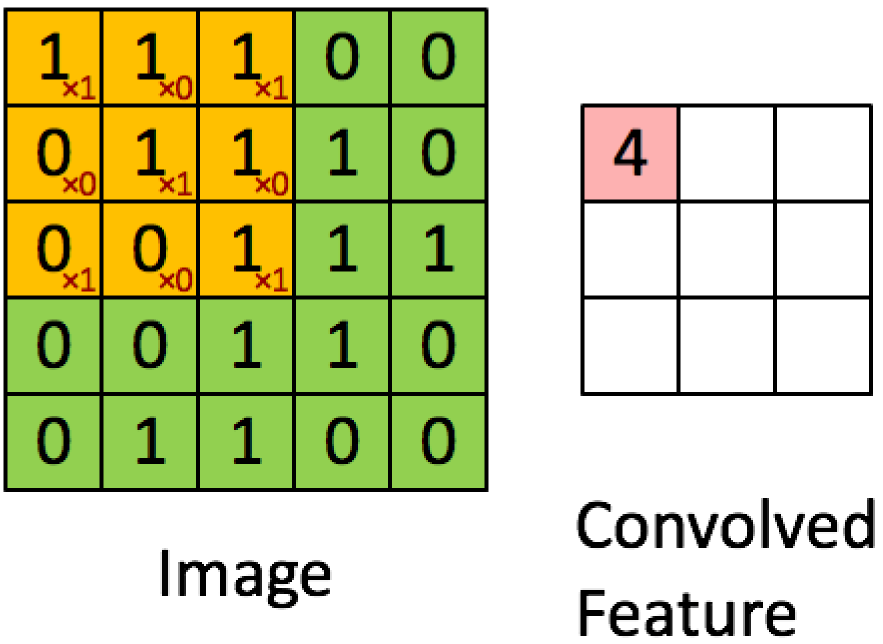

Figure 3.5.3: Convolved feature

Figure 3.5.3. The green box is an image matrix, and the yellow box is a filter, which is a matrix of 0s and 1s that defines a transformation. These features are combined into a feature map as the filter passes through the picture pixels in each subregion of the input volume using a unique type of matrix multiplication.

See this animation to learn more about how the RGB color channel functions.

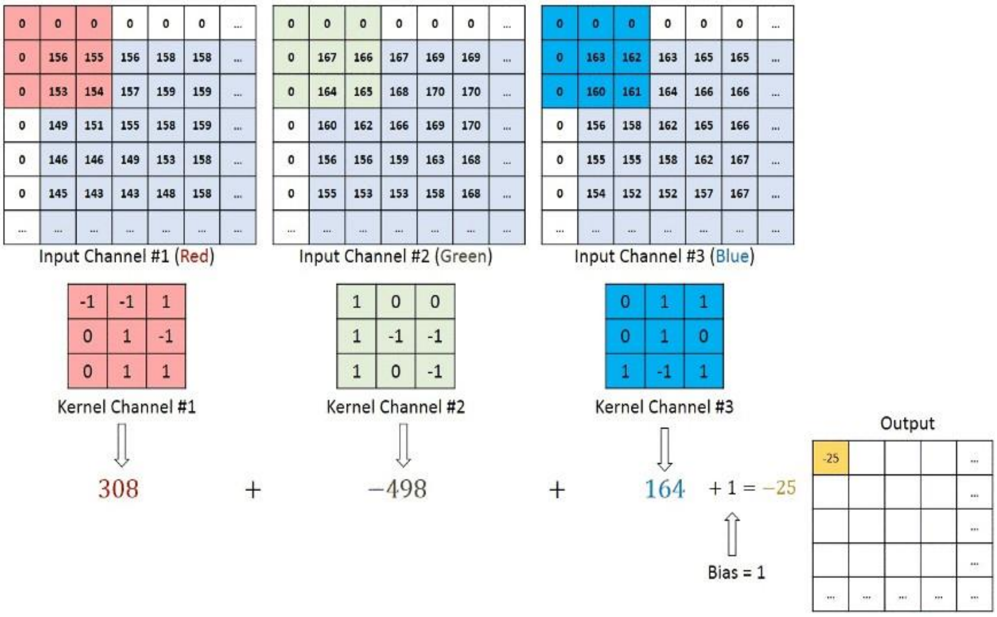

Figure 3.5.4: RGB color

Figure 3.5.4. Convolutional neural networks are made of artificial neurons that are stacked in layers. Similar to their biological counterparts, artificial neurons are mathematical constructs that compute the activation value from the weighted sum of a set of inputs. When an image is fed into a ConvNet, each layer generates a set of activation functions, which are subsequently transferred to thefollowing layer.

Horizontal or diagonal edges are fundamental characteristics that are frequentlyretrieved by the first layer. Following receipt of this output, the following layer searches for more intricate features like corners and multiple edges. As we dig deeper, the network may someday be able to distinguish objects, faces, and other fine characteristics.

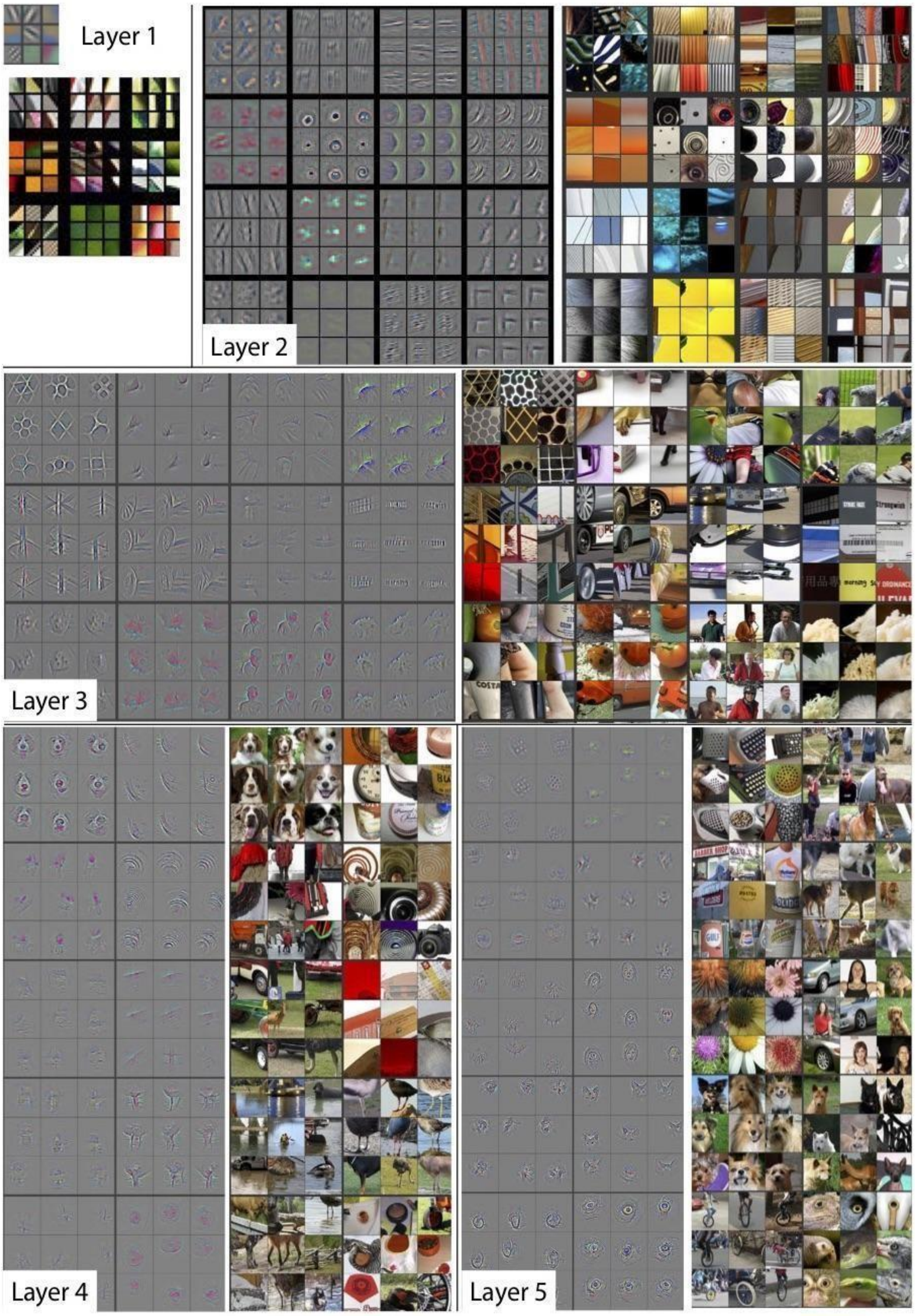

Figure 3.5.5: Classification layer

Figure 3.5.5. Based on the activation map of the final convolution layer, the classification layer generates a number of optimism ratings (numbers between 0 and 1), indicating how likely it is for the image to belong to a "class". The last

layer's output, for example, can be the likelihood assuming the input image contains any of the cats, dogs, or horses detected by the ConvNet.

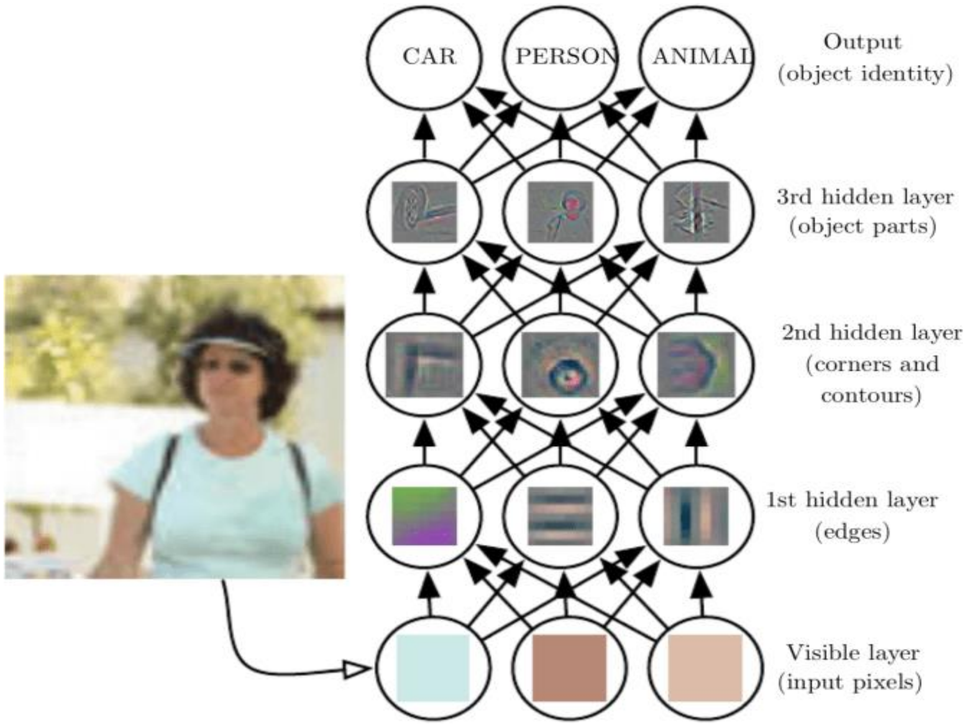

Figure 3.5.6: Final layer
(https://www.ijraset.com/researc
h-paper/suspicious-human-
activity-recognition-and-
alarming-system)

Similar to the convolutional layer (figure 3.5.6), the pooling layer is in charge of reducing thespatial size of the convolutional feature. By reducing the size, less CPU processing power will be required to process the data. There are two types of pooling: average pooling and maximal pooling. I've only used Max Pooling once, but so far there have been no problems.

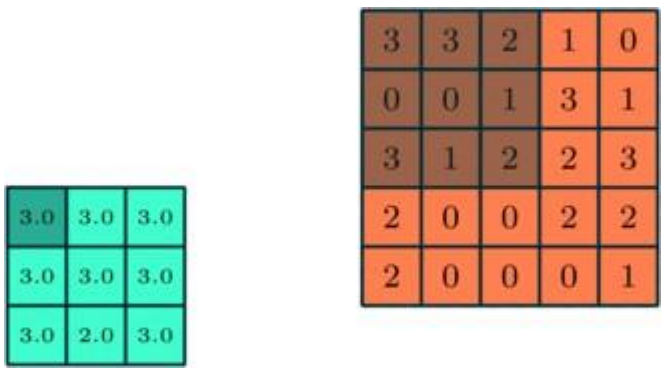

Figure 3.5.7: Polling

As a result, in Max Pooling (Figure 3.5.7), we select a portion of the image that the kernel hascovered in order to find the maximum value of a pixel. Max Pooling also acts as a sound deadener. Along with entirely rejecting the noisy activations, de- noising and dimensionality reduction are also carried out.

On the Figure 3.5.8 average pooling yields the mean of all the values in the region of the image that the Kernel has covered. With average pooling, noise can only be reduced by reducing dimensionality. Therefore, we may say that Max Pooling significantly outperforms Average Pooling.

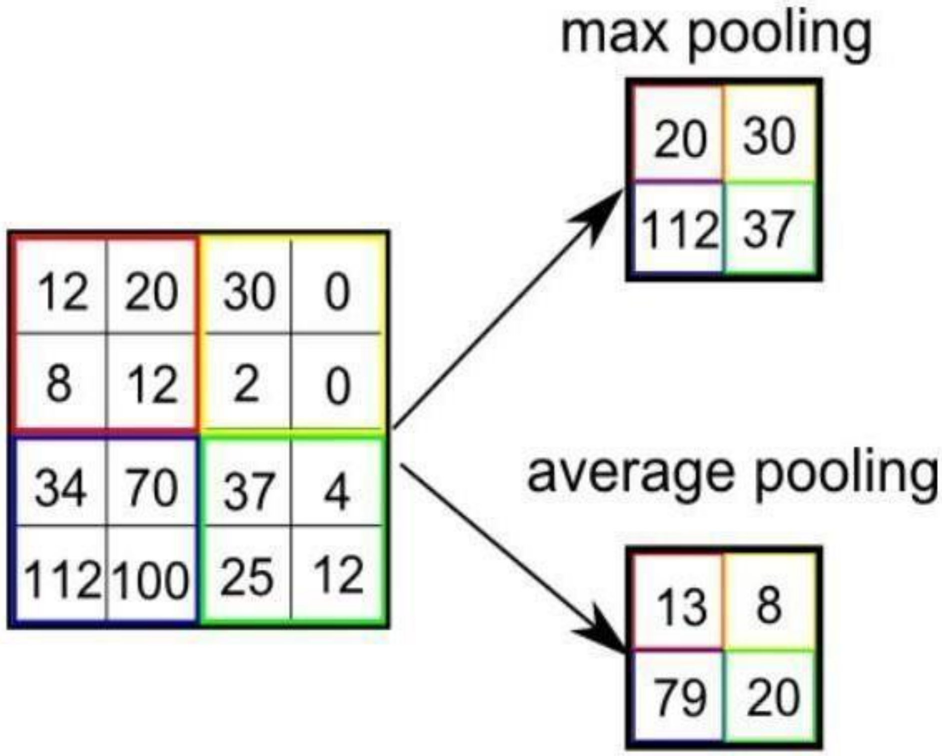

Figure 3.5.8: Polling image

b) Visual Geometry Group-16 (VGG-16):

VGG-16 refers to a 16-layer convolutional neural network. On over a million images from ImageNet's collection, a pre-trained version of the network has been trained . VGG is composed of two fully connected layers, which are recommended by a softmax activation function for the output layer [24]. Many animals, a keyboard, a mouse, and a pencil are among the 1000 possible item categories that may be assigned to photos using a trained network. As a result, the network has accumulated a wide range of feature-rich picture representations. With 97.1% accuracy, the image segmentation and object identification system VGG16 classifies1000 images into 1000 distinct categories.

It is a tried-and-true technique for image classification that is easy to incorporate into transfer learning. Although this form is incredibly straightforward, tasteful, and simple to use, it has shortcomings. The total number of parameters in this model was 138M, and it is more than 500MB. The model's employment is significantly constrained, especially in edge computing, because the compared to similar is longer. Second, the problem of vanishing or expanding gradients is not specifically addressed. Both GoogleNet modules and ResNet's skip connections were used to overcome this issue.

VGG Architecture:

VGG offers two models: the VGG-16 and the VGG-19. In this blog, our datasetwill be classified using VGG-16. VGG-16 is primarily composed of convolution, pooling, and fully linked layers. The input size of thecorresponding network is 224 by 224 [25].

- Convolution layer: In this layer, filters are used to extract features from photos. The most important parameters are the stride and kernel size.
- The pooling layer's task is to shrink a network's spatial extent in orderto scale back on processing and parameterization.
- Fully Connected: These connections to the preceding levels are all fully coupled in a simple neural network.

Given figure shows the architecture of the model:

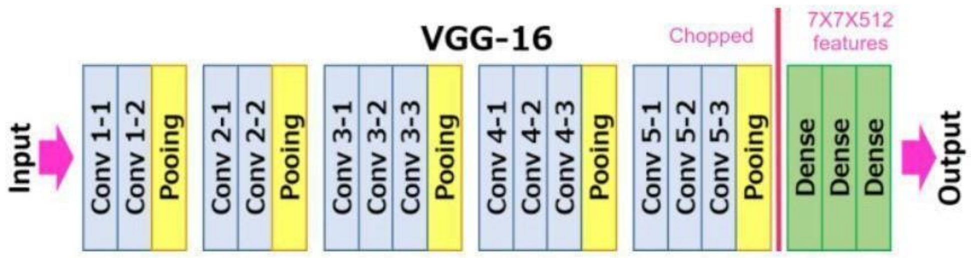

Figure 3.5.9: VGG-16 Layer

Source Import a pre-trained model using PyTorch, Depending on our goals, we can either skip the final fully connected layer or add a new completely connected layer at the end before running the model to include transfer learning.

3.6 Implementation Procedure:

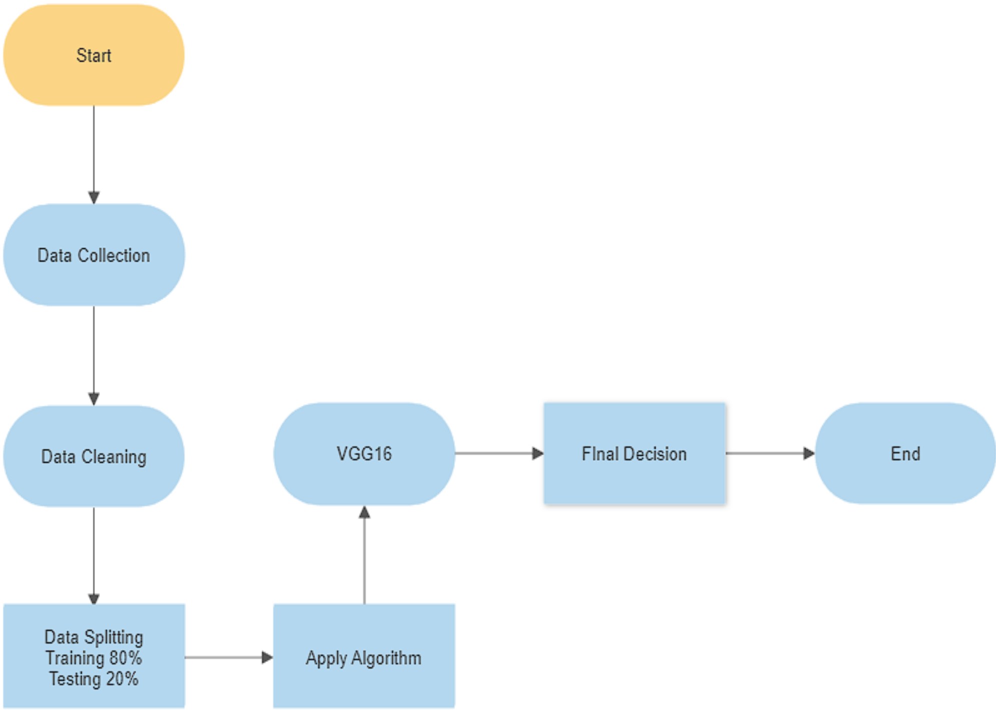

Figure 3.6.10: Flow chart

To begin this procedure, we create a clear diagram that lays out the steps we will take to complete our task. The process was started in the order shown in the diagram, and then we obtained data from Kaggle. Why Kaggle? Since we were unable to locate the real dataset from any institution, we made the decision to focus on the demo datasets in order to gain expertise before moving on to the real datasets. we keep working as per the flowchart diagram.

Figure 3.6.10. Preprocessing of data is the process of cleaning and filtering datasets before applying algorithms to them once they have been acquired. The data sets were then divided into two portions: testing and training, respectively. The training (80%) percentage of the data and the rest (20%) of the data as testing dataset. After completing the process, we have applied two algorithms one is CNN and another one is VGG -16 to find out the associated factors that is causes the brain stroke and the accuracy of the result. Between these two algorithms VGG-16 perform better which isshown in the flowchart.

CHAPTER 4

Experimental Results & Discussion

4.1 Introduction

In the part before, we spoke about the dataset and the methods for processing it. This section will provide an explanation of various models' findings that make use of the prepared data. The results of CNN and VGG-16 are being evaluated to ascertain which method offers the most accuracy.

4.2 Confusion Matrix

A technique for measuring a classification algorithm's effectiveness is the confusion matrix (Table 4.2.1). Classification accuracy alone may be deceptive if our dataset has more than two classes or fewer observations in certain classes than others. We can better understand the successes and shortcomings of the categorization model by developing a confusion matrix. This is the table of confusion matrix:

Table 4.2.1: CONFUSION MATRIX

		Predicted	
		No Stroke	**Stroke**
Actual	**No Stroke**	True Negative (TN)	False Positive (FP)
	Stroke	False Negative (FN)	True Positive (TP)

The following performance metrics are obtained from the segmentation and classifiedresults.

Table 4.2.2: CNN CONFUSION MATRIX

		Predicted	
Actual		**No Stroke**	**Stroke**
	No Stroke	527	51
	Stroke	14	223

Table 4.2.3: VGG-16 CONFUSION MATRIX

		Predicted	
Actual		**No Stroke**	**Stroke**
	No Stroke	557	24
	Stroke	17	221

Accuracy is defined as the percentage of correctly predicted data points among all data points. The official definition of accuracy is as follows:

$$Accuracy = \frac{Number\ of\ correct\ predictions}{Total\ number\ of\ predictions} \times 100\%$$

Binary classification accuracy can also be assessed in terms of positives andnegatives.as shown below:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \times 100\%$$

A machine-learning algorithm's sensitivity reveals how well it can identify favorable traits. The sensitivity, also referred to as the true positive rate, can be computed as follows:

$$Sensitivity = \frac{TP}{TP + FN} \times 100\%$$

Specificity is the proportion of genuine negatives that the model successfully detects. Calculating specificity involves doing the following:

$$Specificity = \frac{TN}{TN + FP} \times 100\%$$

Precision is defined as the ratio of True Positives to All Positives. A formula for calculating precision is provided below:

$$Precision = \frac{TP}{TP + FP} \times 100\%$$

The F1 score is a machine learning statistic that can be used in classification models. The following can be used to calculate the F1 score:

$$F1\ score = \frac{2TP}{2TP + FP + FN} \times 100\%$$

Table 4.2.4. The performance of each algorithm is described in Table 1. Based on the efficiency and validity of different algorithms, we determined the optimal solution for our model. Based on this F1-Score, it is obvious that VGG-16 performs the best in terms of accuracy, sensitivity, specificity, and precision. After considering everything, this approach can be used to optimize model performance.

Table 4.2.4: PERFORMANCE EVALUATION

No	**Model Name**	**Accuracy**	**Sensitivity**	**Specificity**	**Precision**	**F1-score**
1	VGG-16	**97.21** %	93.22 %	**96.02** %	**90.53** %	**91.85** %

4.3 Descriptive Analysis

After going through the entire application algorithm procedure, we finally get a result that shows how important the F1 score, precision, sensitivity, and specificity are.

Whereas the f1 score is composed of two fundamental components, recall and precision, both expressed as percentages and Vgg-16 achieved the best result when coupled as harmonic mean to assign a single number that is simple to understand and performs well in the accuracy matrix. As you can see in the table, CNN performs less because it contains a smaller or no fraction of the larger section. We tested various folding methods in epochs and determined that vgg-16 is the best option for our dataset. VGG-16 shows the highest Accuracy 95.21%, in Specificity VGG-16 shows 96.02%, in Precision VGG-16 shows 90.53%, and in F1-score VGG-16 shows 97.1%. All of those are greater than CNN. On the other hand, in Sensitivity CNN shows 93.64%.

CHAPTER 5

Impact on Society, Environment and Sustainability

5.1 Impact on Society

When it comes to identifying brain strokes, deep learning models have the potential to significantly affect society in a number of ways.

- Enhanced diagnostic precision: These models can quickly and accurately evaluate medical images like CT and MRI scans, minimizing human error and enhancing patient outcomes.
- Faster treatment: Patients can receive care more quickly after being diagnosed with strokes, reducing brain damage and enhancing recovery.
- Reduced workload for radiologists: Deep learning models can automate the diagnosis process, reducing the effort for radiologists and other medical professionals and allowing them to concentrate on other duties.
- Cost-effectiveness: Compared to conventional approaches, using deep learning models to detect brain strokes may be more economical since it eliminates the need for human labor and enhances the effectiveness of the healthcare system.
- Better health outcomes: Deep learning models have the potential to save lives by identifying brain strokes earlier and more accurately.

Overall, using deep learning to brain stroke diagnosis can result in better patient care, quicker recovery times, and better health outcomes, making it an important tool in the medical profession.

5.2 Impact on Environment

By minimizing the need for intrusive procedures and physical examinations, deep learning models for detecting brain stroke can have a beneficial environmental impact by lowering the quantity of medical waste created and the carbon footprint of healthcare. Deep learning models can also assist to increase the precision and effectiveness of diagnoses, perhaps lowering the need for follow-up tests and treatments. But it's important to remember that the environmental effect of deep learning models will rely on the precise deployment and training infrastructure employed, as well as the system's total energy usage.

5.3 Ethical Aspect

When utilizing deep learning models to detect brain strokes, there are various ethical issues to keep in mind. The likelihood of bias in the training data is a significant factor to take into account. The model may give unreliable or biased results if the data used to train it is not representative of the population it will be applied to. Furthermore, there is a chance of overdiagnosis or underdiagnosis, which may result in unneeded therapy or a failure to offer treatment that is required. It's crucial to take into account any potential unintended outcomes, such as prejudice towards particular groups of individuals. It's crucial to make sure that the data used to train the model is representative and varied in order to reduce these risks, and to periodically assess and update the model to enhance performance.

5.4 Sustainability plan

Several crucial elements would be included in a sustainability strategy for deep learning models used to diagnose brain strokes:

- Regularly updating the model with new data to ensure that it remains accurate and up-to-date. This could include new imaging techniques, patient data, and advancements in the understanding of brain strokes.
- Keeping an eye on the model's performance and making changes as necessary. This can entail modifying the training data, the model's parameters, or the model's architecture.
- Ensuring that model users, such as radiologists or neurologists, receive continual training and assistance so they can correctly interpret the model's output and make appropriate diagnoses.
- Exploring ways to make the model more accessible to a wider range of users, such as through cloud-based deployment or mobile app integration.
- Constantly looking for methods to reduce the model's environmental effect, for as by adopting more energy-efficient hardware or looking at alternative deep learning architectures.
- To ensure that the model is producing accurate and trustworthy results, its performance is compared to other diagnostic tools, such as human experts. Additionally, the model is continuously seeking feedback from end users, such as radiologists or neurologists, in order to identify areas for improvement and make necessary adjustments.

CHAPTER 6

Conclusions & Future work

6.1 Conclusions

Segmenting medical images is a challenging challenge because of because of how complicated the images are and because there aren't any anatomical models that can accurately represent all of the deformations in each component. The initial cluster size and cluster centers can be successfully managed with the help of the suggested technique. In order to segment, BWT techniques are utilized, which have lesser accuracy and processing speed. This research offers an almost entirely automated method for dividing brain tissue. This suggested method's main goal is to enable neurosurgeons or human experts to quickly identify the patients. The experimental findings show that the accuracy is 98.5 percent greater than that of cutting-edge technologies. The processing time, system complexity, and memory space requirements of the techniques can all be further decreased. The similar approach can be used to recognize and investigate diverse conditions present in other body areas (kidney, liver, lungs, etc.). Future studies can combine greater segmentation and extraction efficiency algorithms with real time photos, clinical cases, a larger data set with a range of settings, and different classifiers that apply optimization methodology to boost accuracy.

6.2 Future Work

Due of several restrictions, we are unable to completely clear the dataset or add more algorithms at this time. But since we haven't encountered it. In order to use additional algorithms and achieve the best accuracy, we must look further. And this can assist humanity in finding a solution to the "Brain Stroke" disease problem not just in this country but throughout the world. And this firmly maintains that we can use the algorithm to accomplish much greater accuracy before we can primarily serve it over the world.

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Brain stroke

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