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Brain Tumour Detection and Classification by using Deep Learning Classifier

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Abstract: When it comes to the field of medical image processing, the classification of brain tumours is one of the most significant and difficult problems to solve. As a result of the fact that manual classification with the assistance of humans might result in incorrect diagnoses and forecasts. In addition to this, whenever there is a substantial amount of information that must be processed manually, the process develops into a lengthy activity that is difficult to complete. As a result of the fact that brain tumours can take on a wide variety of forms, as well as the fact that there is a certain degree of similarity among normal and tumor tissues, it can be challenging to distinguish sections of a patient's brain that contain tumours from scans of that brain. As a result, a model is constructed to detect brain tumours from 2D magnetic resonance images of the brain by utilising a hybrid deep learning technique. This methodology is then accompanied with both traditional classification techniques and deep learning approaches. The application of the concept in clinical settings is the ultimate goal. The research was carried out using a Kaggle and BRaTS MICCAI dataset that had a wide range of tumours, each of which had its own size, location, and form, in addition to differing levels of image intensity. A total of 6 various classification methods namely Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Multi-layer Perceptron (MLP), Logistic Regression (LR), and Naive Bayes (NB) were used when doing the conventional phase of categorization. When compared to these conventional classifications models, the SVM produced the most accurate results. After that, a Convolutional Neural Network (CNN) is used, which, when compared to the traditional classifiers, shows a significant enhancement in overall performance. Various Layers of CNN using different split ratio of dataset was evaluated. It is observed from the experimental findings that 5 layered CNN can obtain the highest performance accuracy of 97.86% using 80:20 split ratio.

Keywords: Brain Tumor Detection, Magnetic Resonance Images, Machine Learning Classifiers, Deep Learning Classifiers, CNN.

1. Introduction

The brain is one of the many organs that make up the human body, yet it is by far the most significant and important of these organs [21]. Among the most prevalent factors contributing to neurological impairment is the presence of a tumour. A malignant growth, sometimes known as a tumour, is simply an abnormal development of cells. The cells that make up a brain tumour grow in such a way that, in the end, they absorb all of the nutrients that was supposed to go to the regular cells and tissues, which leads to malfunction in the brain [21]. Based on the data on the death rate caused by brain tumours, it is one of the most harmful and devastating forms of cancer that may occur in the body. More than one million people around the world are diagnosed with brain tumours each year, and the death rate associated with these tumours is steadily increasing, as reported by Global Cancer Research. It is the second leading cause of death in children and young adults under the age of 34 years [1]. In recent decades, practitioners have been using advanced techniques in order to discover tumours that cause patients more discomfort. Scanners that use Computed Tomography (CT) and those that use Magnetic Resonance Imaging (MRI) are two examples of useful instruments for locating issues in different parts of the body [22]. In latest years, MRI-dependent medical image processing has become incredibly common for use in the research of brain tumours. This prominence can be attributed to the growing demand for efficient and objective evaluation of huge amounts of data in the healthcare industry. In order to investigate such a diverse selection of image formats, it is necessary to make use of sophisticated digital evaluation and visualisation strategies. As a consequence of this, accurate automatic diagnosis derived from MRI scans would play an important part in this case since it will eliminate the requirement for human ways of processing massive volumes of data [22].

The proposed research project is based on such a system, which makes use of computer-based methods for identifying brain cancers and classifying tumour kinds by making use of MRI images from a variety of patients and

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employing a hybrid form of deep learning. The identification of brain tumours in cancer patients' MRI scans is accomplished by the use of image processing techniques such as picture fragmentation, image augmentation, and the feature extraction [22]. Pre-processing, fragmentation, feature extraction, and classification are the four primary stages involved in the process of diagnosing brain tumours through the use of an image processing approach. In order to improve the efficiency of brain tumour recognition and characterisation in MRI images, image processing and Neural Network (NN) methods are used.

The strategy for doing the research that has been suggested includes a number of objectives, the primary among which is to build a model that is able to determine if or not the MRI scans contain a tumour and locate the characteristics of the tumour. When operating on a medical image, the collecting of datasets is the most important task that needs to be finished in order to progress [26]. This is because there is very little information available on brain tumours, and acquiring this information is incredibly challenging. The vast majority of the investigators focused their attention on activities that would lead to definitive results, like filtering, fragmenting, feature selection, and skull extraction [23, 24, 25]. A model is developed which is capable of executing all of the basic and main activities that are necessary to find a tumour and define the characteristics of it. These tasks are important in order to diagnose cancer. A novel strategy that is both effective and productive has been proposed, and it is one that makes use of both traditional classifiers and the Convolutional Neural Network. This approach helps in the classification of brain tumours as well as the detection of them, and it does it completely independently of any involvement from humans. In the last stage of the process, all of the results of the tests are compared to one another in order to establish whether or not the model provides superior performance in terms of accuracy and any additional performance indicators. The paper is divided into several portions. In the following part II the relevant work done by a number of different researchers is examined. In part III, a description of the framework of the proposed system is provided. In section III, proposed system framework is described. The experimental result and discussions are described in Section IV. The proposed work is brought to a conclusion in Section V.

2. Literature Survey

V. Sravan et al. [2] provide a variety of approaches for classifying MR brain images, ranging from straightforward cutoff methods to more complex methods such as deformable methods and hybrid approaches. These methods range in complexity from elementary to advance. The system is geared toward discovering and identifying brain cancers at the earliest possible stage. It discusses a number of investigations involving the segmentation of brain tumours, in addition to Deep Learning (DL) techniques such as CNN. Ishita Maiti et al. [3] came up with an innovative method for locating brain tumours in patients. For this purpose, the watershed technique is utilised in combination with the edge detection algorithm. It is a technique for detecting brain tumours that is based on colour and makes use of the HSV colour system. The picture is converted into an HSV colour image, which is then divided into three distinct zones based on their hue, saturation, and severity values. After the contrast has been brought out more, the watershed technique is used for each and every image. A Canny edge detector is applied to the image that was produced as a consequence. The three images are integrated into one another to generate the definitive fractured image of the brain tumour. Twenty different brain MRI images were examined in order to validate the method. The programme that was developed has produced outcomes that are cause for optimism.

According to R.Tamilselvi et al. [4,] BRAMSIT is a software that members of the research community who evaluate MRI images can utilise. The BRAMSIT dataset is an MRI dataset that is currently in the planning stages and seeks to give a collection of photos of benign and malignant brain tumours. The repository is responsible for providing interpretations of information such as the age of patient and the MRI axial position. A unique Ultra-Wideband (UWB) patch antenna built on graphene based conductor was proposed by Ahasan Ibna Aziz et al. [5] as a method for detecting human brain tumours in the year 2019. The 3.15 to 9.15 GHz frequency range is covered by the newly developed ultra-wideband patch microstrip antenna with a radiating patch. Since the beginning of time, people have believed that the lengths of the ground patch are the single most essential component in determining how well an antenna would perform in terms of its overall coefficient of reflection. The designed antenna is placed at a distance of 20 mm as from human head and uses a 6-layered human skull method to detect cancer cells within the skull. The human skull is spaced 20 mm away from the antenna. Readings of the coefficient of reflection that are lower than those that are greater when compared to those that are lower show the presence of a brain tumour, whilst higher amounts suggest the absence of a brain tumour. The biocompatibility of cerebral tissue can be evaluated through the use of the CST MWS program. CNN architecture for the detection of brain tumours was presented by Gajendra Raut et al. [6]. The proposed model was trained using pre-processed MRI images of the brain, and it employs the model that was retrieved during training to categorise newly acquired image data as either healthy or tumorous. During the training phase, back propagation has been utilised to improve accuracy while simultaneously reducing the number of mistakes that are being made. In order to build the image, autoencoders are used to filter out undesirable effects. After that, the tumour region is segmented using the KMeans technique, which is an unsupervised learning approach.

Deepa P. L. et al. [7] created methods for accurately detecting cancers by depending on pretrained network topologies such as ResNet and its variations. The discovery demonstrates that ResNet-152 represents the most successful method in terms of accurately detecting cancers, and that the process might be even more effective with the implementation of automation.The goal of the research conducted by Divyamary.D et al. [8] is to develop a method that is capable of detecting brain cancers in their earliest stages. Noise removal, morphological procedures segmentation oriented, feature extraction, and a classification algorithm called Naive Bayes (NB) are a few of the processes that are involved in the research. A preliminary processing step is performed on the image that was captured, followed by the extraction of features. As a consequence of this, the Naive Bayes classification method is applied in order to arrive at accurate estimates of brain tumours. There are a variety of techniques that can be utilised in MRI scans to identify the presence of brain tumours, as stated by Ms. Swati Jayade et al. [9]. These approaches face a wide variety of challenges, the most significant of which is locating and measuring the tumour accurately. When attempting to locate a tumour in an image of the brain, picture segmentation can be helpful. Numerous methods for the segmentation of images have already been developed and demonstrated to be effective through experimentation. This research article addresses the core principles and procedures of identifying brain tumours using MRI scans, in addition to a description of the many approaches that can be used to fragment brain tumours.

Aya S. Derea et al. [10] describe a constructed technology that can identify and classify brain cancers. The segmentation-based cutoff that is applied to the images produced by MRI scans in order to locate the region of interest Texture features are obtained through the utilisation of a Grey Level Run Length Matrix (GRLM), and tumours in MRI pictures and features images are recognised by the application of a segmentation dependent threshold approach. MRI was used to identify the site of the tumour as well as its features using the histogram. Behavior complementing photos were also taken for each characteristic. The dimensions, location, area, and measures are all included in the list of geometrical attributes that make up the tumour image as well as the complementary image. On the basis of the segmentation strategy that was applied, the recognition performance was extremely successful in partitioning the entire tumour area. When GRLM is used, the separation of the tumour area from the complementing area enables an extraordinary level of accuracy in the surface feature quality. According to research done by Soumya S. Pillai et al.[11], doing medical imaging or evaluation requires performing a wide variety of computations, the accuracy of which is most dependent on. In order to get greater precision in the analysis, the suggested strategy seeks to get rid of computational geometric difficulties. In most cases, problems manifest themselves during the process of picture segmentation, shape assessment, three-dimensional modelling, and volumetric validation of data. Con-formal geometric algebra provides a robust framework for coping with all of these challenges, which is a significant advantage. The images that were obtained as a result of the MRI scan were two-dimensional pictures in which the tumour has to be located. This discovery provides a key to recognizing brain regions where tumour growth has occurred and to building a 3D modelling of the tumour for reference in the future. This could help medical professionals more effectively treat people who have been impacted by tumours. The generation of a two-dimensional picture followed by the elimination of noise is the initial step in the process of accurately determining whether or not brain-related regions contain tumours.

A research on the tumor detection locations by the use of Morphological Operators based fragmentation techniques was performed by Rakshanda M. Mapari et al. [12]. It contains procedures for upgrading, dividing, and putting things in place. In order to zero in on the area occupied by the tumour, the images are segmented and categorised according to whether or not it is benign or malignant. If there are a significant number of photographs, medical professionals can cut their work time in half by using this technique. Feature Concatenation based Squeeze and Excitation-GAN (FCSEGAN) is what Thirumagal E. et al. [13] recommend using for MRI brain tumour segmentation in the year 2020. The recommended network neural architecture makes use of ResNet as its foundation. In order to obtain sharp MRI scans, it combines the typical combination technique with the producer. Additionally, it integrates the compression as well as stimulation block with the determiner in order to split the area occupied by the brain tumour. Using a Brain MRI picture dataset obtained from Kaggle, the research was conducted out on FCSE-GAN, WGAN-GP, and Info-GAN designs, respectively. Based on the results of the studies, FCSE-GAN is superior to both WGAN-GP as well as Info-GAN in regards of its efficiency, accuracy, and recall, as well as its F1 measure. Ritu Joshi et al. [14] suggest a characteristic learning strategy that will boost the effectiveness of a machine learning method for determining brain tumour locations at the pixel level in MRI images of the brain. This system employs methods for attribute extraction that are based on picture filtering in order to construct subspaces. Following that, the feature space is converted to a response set that contains certain tags. Following the construction of the feature space and the response set with the help of a reference point derived from a quantitative MRI image, a machine learning model may then be trained using the data. In order to find tumour and non-tumor areas in extra blocks of the MRI image, it used both the trained models and automated techniques. The datasets from Brain Tumor Segmentation (BraTS) are utilised in the process of developing and evaluating the computational system that has been constructed. In addition to that, it took use of the real truth labels contained within the BraTS 2015 datasets. In order to evaluate the ANN, RF, and SVM algorithms, a variety of quantitative and qualitative criteria were utilised. It was determined, based on the precision-recall curve, that the RF system gained 92 percent of the tumour recognition abilities of a perfect system, while ANN and SVM achieved 90% and 88% of the tumour recognition skills of a perfect model, respectively. This was done in comparison to the RF system, which gained 92 percent of the tumour identification skills of a perfect system.

Md. Abu Bakr Siddique et al. [15] proposed the use of a deep CNN deployment for the purpose of diagnosing brain cancers from MR images. The dataset that was used in this research consisted of 253 MR images of the brain, with 155 of those images displaying malignant tumours. Our method is capable of recognising tumours in MR images with a precision that is equivalent to 96 percent. With an accuracy of 0.93, a responsiveness of 1.00, and an F1-score of 0.97 in the test dataset, the system was capable of identifying brain tumours more effectively than the conventional methods that were previously used. The proposed model can provide assistance to clinical specialists in determining if a person has a brain tumour and, as a consequence, can accelerate the process of developing a therapeutic strategy. Mohammad Omid Khairandish et al. [16] intend to investigate the effectiveness of machine learning techniques in the diagnosis and treatment of brain tumours. Research is carried in every study with regard to the method type, dataset, proposed method, and efficacy. The accuracy of the papers that were evaluated in this survey ranged anywhere from 79% all the way up to 97.7%. They proceeded with the CNN, KNN, C-means, and RF approaches in that order, moving from the method that was used the most frequently to the one that was used the least frequently. In the research that were looked through, it was found that alternative methods were used, and they produced satisfactory results. In spite of this, it is still necessary to establish confidence in the outcomes of the study on their efficiency in detecting brain tumours. In addition, the development of software utilisation can be highly helpful in finding solutions to problems that occur in the actual world. Aryan Sagar Methil et al. [17] propose a one-of-a-kind approach to the diagnosis of brain cancer from separate images of the brain. In this approach, multiple image pre-processing methods, including histogram equalisation and aperture, are used in conjunction with a CNN. In addition to this, the study discusses the impact that various picture preparation methods had on the datasets, including those that were not authorised for use in training. A dataset containing a variety of tumour types, diameters, patterns, and placements was used for the testing. In order to complete the categorising task, a CNN was utilised. During the trial, CNN achieved a recall of 98.55 % on the training dataset and 99.73 % on the testing dataset, which is a very excellent result.

Chirodip Lodh Choudhury et al. [18] proposed research to be conducted in 2020 that makes use of a DNN methodology and incorporates a CNN dependent method in order to forecast whether an MRI will show a "Tumour Recognised" or "Tumour Not Recognized." The algorithm achieves an overall accuracy of 96.08 percent, which corresponds to an f-score of 97.3.Preeti Sharma et al. [19] presented a methodical and polite analysis of different approaches to the classification of brain tumours. The recommended method demonstrated tumour detection by CAD because manual detection is difficult.

3. Proposed System

The proposed system's architecture is depicted in figure 1. This demonstrates how the proposed system needs to be implemented in order to detect a variety of visual defects utilising CNN. The whole framework illustrates how the system functions by demonstrating identification and detection of test images, and the technique of execution is discussed in more detail below.

The purpose of this research is to combine traditional feature selection techniques with Machine Learning (ML) in order to identify potential illnesses. The early diagnosis of abnormalities in MRI, CT scan, and X-ray images is made possible by this system because to its use of image processing and deep learning techniques. The dataset, which had flawed pictures from a variety of locations, was pre-processed and separated before feature extraction could take place in an effective manner.

Image Acquisition: Acquiring an image entails accumulating disparate pictures of clinical datasets that contain abnormal and healthy specimens from a variety of people and transforming them into digital form by the use of a camera or some other synthetic dataset.

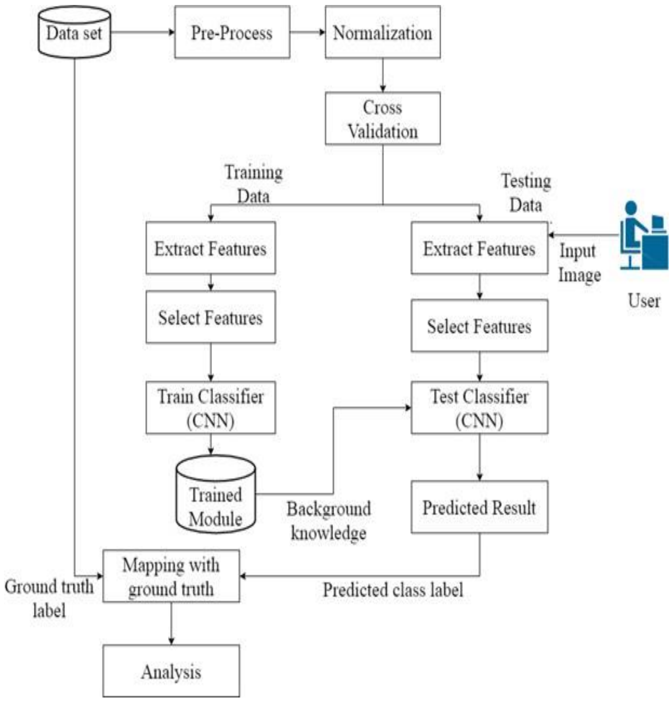

Fig. 1. Proposed System Technique for classification using CNN

Pre-processing: Due to the fact that the input data samples were gathered from a diverse group of individuals, there is a possibility that there will be problems such as deformation and picture blurring, in addition to other difficulties. As a consequence of this, pre-processing techniques are utilised on photographs in order to reduce the amount of noise and enhance the image quality by using a fresh approach. The difficulty in changing the image is due to the fact that it was originally saved in the RGB colour format. The RGB to grey scale conversion is required in order to reduce the complications of a pixel value that has three dimensions to a value that has only one dimension. In many situations, such as edge identification, the utilisation of three-dimensional pixels does not offer any distinct advantages.

Extraction of Features: There are a total of six unique photo collections that were assembled from a variety of data sources. After the photos have been taken, they are processed using various imaging methods in order to get data that will be useful for subsequent research. In order to ensure that the preprocessing is carried out as effectively as possible, it is necessary to scale all of the obtained pictures to the same dimensions. After the RGB photos have been scaled, they are then changed into a kind that uses hue, saturation, and intensity. The utilisation of a depiction in space based on hue, saturation, and intensity brings to a significant improvement in colour perception. After that, the masking tool is used to erase the pixels. The practise of altering the pixel value of an image so that it is either 0 or one of the adjacent values is known as masking. After that, the approach known as K-means fragmentation is used to split the damaged region of the initial image. The objective of segmentation is to transform the representation of a picture into a relevant image that can be analysed in a more straightforward manner. The most useful characteristics from the dataset are then selected using a method called feature selection to ensure accurate classification. PCA, Information Gain, and Relief-f Attribute Analyzer are the three feature selection approaches that were utilised.

Feature Selection: In both image processing and data mining, selection of features is an extremely important step. It does this by taking the original data and generating the optimum subset of predicted features. A subset of the original features is chosen, with the goal of preserving sufficient information in order to differentiate across classes in an efficient manner.

Classification and Recognition: Disease categorization refers to the process of determining the appropriate label for a test sample and recognizing it as belonging to the appropriate class. The output of the module responsible for the feature extraction is used as an input in the classification algorithm. The classifier will identify the proper class label for the source photos after gathering a variety of information to use in its analysis. There are many different approaches used for classification. DL is the name of one of them. The neural networks used in deep learning include CNN, ANN, RNN, and others. The image is then sent into a CNN, which extracts the features that are most important and splits them into layers. The primary benefit of CNN is that it reduces the amount of manual labour that is required of people in order to extract attributes. As a consequence of this, the method that has been presented makes use of a CNN, to detect brain cancers.

In order to evaluate how well the CNN model that was proposed actually performs, the following algorithm has been used:

Algorithm of proposed CNN Model

1. loadData();
2. dataAugmentation();
3. SplitInfo();
4. loadInfo();
5. for each epoch in epochN do
6. for each batch in batchlength do
7. $\hat{y}$ = model(attributes);
8. loss = crossEntropy(y,$\hat{y}$);
9. optimization(loss)
10. Accuracy=(1-loss)*100%
11. end
12. end

4. Result and Discussion

Kaggle and BRaTS MICCAI dataset are used in the proposed research methodology which is explained as follow,

Kaggle Dataset - Images may be uploaded in the form of.csv or.dat files; it may be monochromatic, RGB, or HSV; or it may simply be in a.zip file, as is the case with the web Kaggle dataset. There were 155 tumour MRI images and 98 normal MRI photographs included in the report.

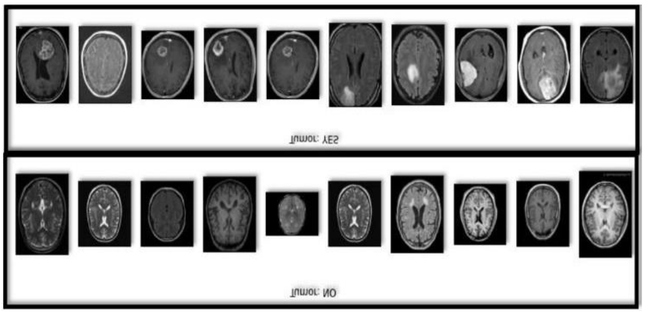

Fig. 2. Online Kaggle Dataset

BRaTS MICCAI dataset: The BRaTS project of the MICCAI has historically centred its attention on assessing innovative techniques for the segmentation of brain tumours in MRI images. A substantial quantity of clinically collected multimodal MRI images of glioblastoma and lower grade glioma from several institutions were submitted for use in the training, validation, and testing phases of the BRaTS task. These data included a pathologically conclusive diagnosis and open access OS. Each of the BRaTS multimodal imaging is available to be viewed as NIfTI files, and each of these multimodal scans defines T1, T1-weighted, T2-weighted and T2 FLAIR volumes. These multi - modal scans were obtained by utilising a wide range of clinical methods and imagers that were stored in an assortment of various locations. It presented a set of images that were taken before and after the surgery, along with ground truth tags that were produced by integrating the findings of various segmentation approaches.

Each of the MRI imaging datasets were manually separated by between one and four raters using the same labelling technique. Additionally, all of the marks on the datasets were examined and validated by qualified neuroradiologists. Annotations have been made on the whole tumour, as well as the tumour centre and the augmenting tumour centre. The dataset is split up into two separate files: one for the training dataset, and another for the testing dataset. The 'train' file contains 220 HGG persons and 27 LGG persons spread across two subfolders. Together, these make up the HGG and LGG situations. The folder labelled "test" contains photographs of the brains of 110 people who had HGG as well as LGG manifestations. There are five separate MRI image modalities that are taken of each and every patient: T1, T1C, T2, FLAIR, and OT.These image files were all converted to the .mha format, have a resolution of 240 by 240 pixels and had their skulls removed. In the images that represent the ground truth, each voxel is given a label that specifies whether it is a zero or a nonzero. These labels refer, respectively, to ordinary pixels and portions of tumour cells.

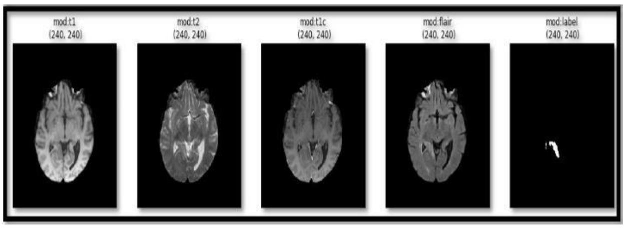

Fig. 3. Online BRaTs Dataset

The BRaTs dataset is utilised in the application of the suggested approach. This is a tagged dataset that makes a distinction between tumours and other types of tissue. There are two distinct parts to the dataset, which are the training dataset and the testing dataset. The photographs have been classified into the following categories: T1-weighted, T2-weighted, and FLAIR. Each set is comprised of two distinct classes. The first one is a tumour MRI (class 1), and the second one is an MRI without tumours (class 0). In the training dataset, there were a total of 187 MRI images of tumours and 30 MRI scans that did not show any tumours. In addition, there are 24 test images included for use in the performance assessment.

Experiment – I

In the initial test, ratio of 70:30 was used to divide the dataset. This means that 70 % of the data was used for training, while 30 % of the data was used for testing. This ratio is utilised in order to provide an assessment of how effective the model presented in Table 1 is. It has been shown that SVM generates the most accurate results.

Table 1: Performance Measurement using ML Classifiers (based on ratio of 70:30)

Classifiers	Accuracy	Recall	Specificity	Precision	Dice Score	Jaccard Index
KNN	0.8935	0.945	0.427	0.932	0.941	0.887
LR	0.8785	0.944	0.284	0.916	0.934	0.873
MLP	0.8935	1.002	0.163	0.895	0.942	0.892
NB	0.7874	0.795	0.712	0.959	0.866	0.768
RF	0.8935	0.981	0.164	0.916	0.943	0.890
SVM	0.9234	0.983	0.423	0.938	0.957	0.921

The data are split into a 70:30 ratio in order to facilitate the implementation of the suggested 5-layer CNN classification model. Table 2 illustrates how the learning rate, model accuracy, number of epochs, and total amount of time spent training are related to one another depending on the splitting ratio. Whenever the learning rate was set to 0.001, the epoch was set to 50, and the training time was set to 500 seconds, the highest suitable result was produced. The accuracy of 96.55 % was achieved by utilising this split ratio.

Table 2: Accuracy and Training Time of the proposed CNN approach (based on split ratio of 70:30)

Learning Rate	Epochs	Training Time (sec)	Accuracy (%)
0.001	10	180	92.88
	20	231	93.23
	50	500	96.55
	100	1227	96.01
0.005	10	198	93.00
	20	240	93.13
	50	555	90.68
	100	1133	91.22
0.01	10	191	88.76
	20	235	90.92
	50	634	91.25
	100	1347	93.45

Experiment – II

During this stage of the process, the dataset is split in ratios of 80:20 so that the proposed five-layer CNN classification model can be built. Table 3 provides an analysis of the amount of time necessary to complete training as well as the level of accuracy achieved, taking into account both the epoch and the learning rate. When the epoch & learning rate are set to 10 and 0.001 correspondingly, the accuracy gained is 96.55 %, and the training time is 174 secs.

Table 3: Accuracy and Training Time of the proposed CNN approach (based on split ratio of 80:20)

Learning Rate	Epochs	Training Time (sec)	Accuracy (%)
0.001	10	174	97.86
	20	232	97.86
	50	526	95.75
	100	1201	95.68
0.005	10	176	96.02
	20	202	97.61
	50	487	95.54
	100	1026	95.54
0.01	10	177	92.08
	20	201	93.03
	50	598	93.76
	100	965	92.01

Experiment-III (5-layer CNN Design)

In addition, in order to create the suggested model for a 5-layer CNN, a large number of study observations are included that are dependent on many hyperparameters, like splitting ratios. Table 4 illustrates how successful a 5-layer CNN model can be depending on whether or not the split ratios are 80:20 or 70:30. According to Table 4.6, the approach reaches a satisfactory level of accuracy of 97.86 % when the splitting ratio, batch size, and epoch are set at 80:20, 64, and 10, respectively. After this level, the algorithm begins to produce results that are too good to be true. Therefore, by utilising a 5-layer CNN framework, an accuracy of 97.86 % is obtained.

Table 4: Performance of the proposed 5-layer CNN model

Convolution Layer	Max Pooling	Split Ratio	Batch Size	Epoch	Accuracy (%)
62*62*32	31*31*32	80.20	32	8	**92.71**
				9	85.81
				10	86.84
				11	87.87
			64	8	93.66
				9	94.97
				10	**97.86**
				11	94.88
		70.30	32	8	81.34
				9	83.70
				10	87.86
				11	**89.12**
			64	8	88.06
				9	88.75
				10	91.22
				11	**94.91**

Experiment-IV (6-layer CNN Design)

At this stage, another 62*62*32 convolutional layer is being added to the network. Altering the dimensionality could provide an erroneous model as a result. Using two convolutional layers, one max pool layer, one flatten layer, and two fully connected layers allows to achieve the highest level of accuracy possible, which is 94.38 %. In the case where the split ratio was 80:20, the batch size was 64, and the epoch was 11. Table 5 provides the most accurate results for us. After reaching this point, the accuracy of the system started to become less reliable. As a consequence of this, expanding the number of convolutional layers will not lead to improvement in accuracy.

Table 5: Performance of 6-layer CNN model

Convolution Layer	Max Pooling	Split Ratio	Batch Size	Epoch	Accuracy (%)
62*62*32	31*31*32	80.20	32	8	89.28
				9	92.82
				10	**93.75**
				11	93.61
			64	8	94.02
				9	94.07
				10	**94.38**
				11	94.20
		70.30	32	8	82.38
				9	83.70
				10	**84.23**
				11	86.16
			64	8	**88.26**
				9	82.22
				10	81.68
				11	80.06

Experiment-V (7- Layer CNN Design)

A 7-layer CNN model (2-convolutional, 2-max pooling, 1-flatten, and 2-fully connected layers) is used to determine the effectiveness of diagnosing brain tumours. This model consisted of two convolutional layers, two max pooling layers, one flatten layer, and two fully connected layers. The Max Pooling layer was increased because it was discovered in the most recent test that adding more convolutional layers to the model did not result in an improvement in its overall performance. According to table 6, the highest level of accuracy, expressed as a percentage, can be achieved by setting the splitting ratio to 80:20, which results in a batch size of 64 and an epoch of 9, correspondingly.

Table 6: Performance of 7-layer CNN

Convolution Layer	Max Pooling	Split Ratio	Batch Size	Epoch	Accuracy (%)
62*62*32	31*31*32	80.2	32	8	88.16
				9	**90.15**
				10	89.01
			64	8	95.32
				9	**95.66**
				10	95.2
				11	94.98
		70.3	32	8	79.72
				9	84.16
				10	**84.37**
				11	84.3
			64	8	87.06
				9	87.11
				10	**87.18**
				11	87.17

Model Validation

Two different graphical representations are provided in the following figures, each of which is dependent on the 70:30 split ratio of the proposed Convolutional Neural Network model which makes use of the BRATS dataset. Figures 4 and 5 have a split ratio of 70:30 between them.

Figure 4 depicts the loss curve that was produced when the training curve and the validation curve intersected during the stage of the epoch that came before it. As a consequence of this, right from the start, the validation rate is not related to the validity of the model, which is something that the system does not desire.

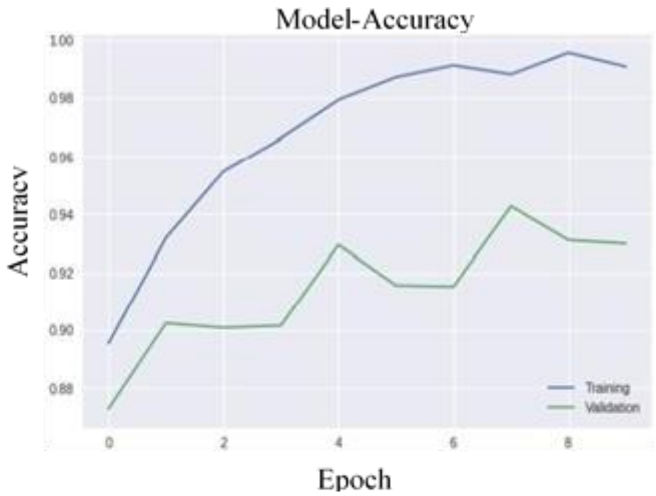

Figure 4: Model Accuracy curve based on split ratio of 70:30 (using BRATS Dataset)

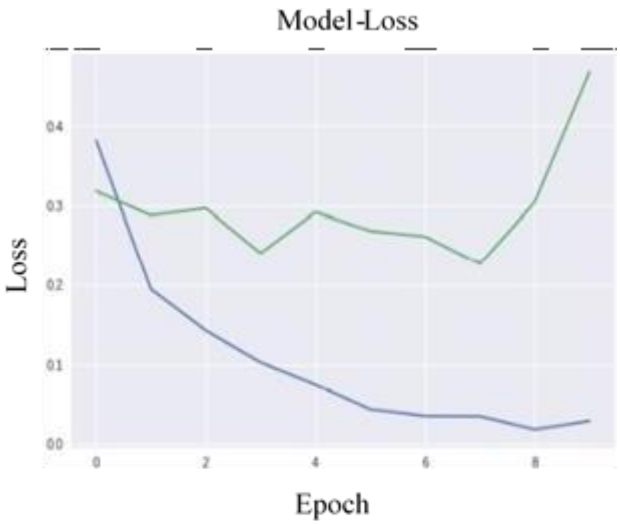

Fig. 5: Model Loss Curve based on split ratio of 70:30 split (using BRATS Dataset)

Figure 6 illustrates how well each of the six approaches performed when compared with a distribution ratio of 70:30. In this particular scenario, the support vector machine yields the best results.

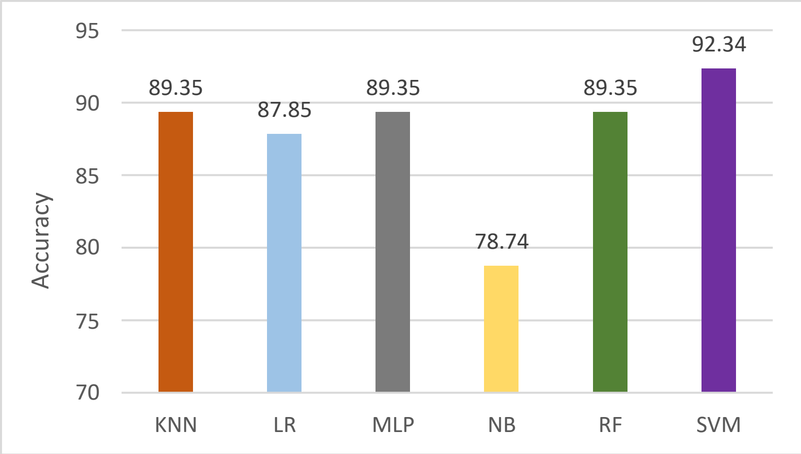

Fig. 6: Performance Accuracy by using ML classifier based on split ratio of 70:30

Figure 7 displays a bar graph that compares the learning rate to the amount of time spent training. The three different numbers for the learning rate was determined depending on this split ratio: 0.001, 0.005, and 0.01. As one's learning rate rises, the amount of time spent in training will naturally decrease. The training time is equal to 180 seconds when the learning rate and the number of epochs are 0.001 and 10 correspondingly.

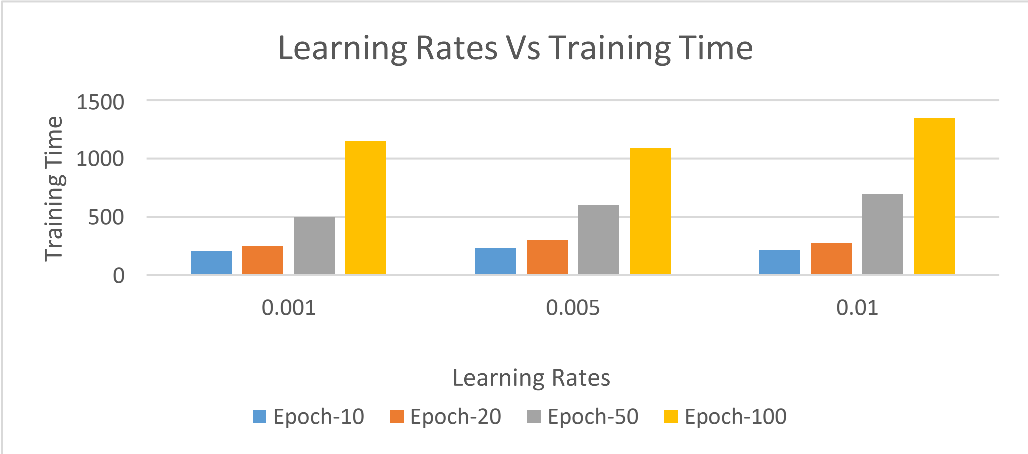

Fig. 7: Learning Rate versus Training Time of proposed CNN approach (based on split ratio of 70:30)

Figure 8 demonstrates the accuracy of the results. The four different epoch values were chosen depending on the split ratio: 10, 20, 50, and 100. The highest level of accuracy i.e 96.55 % is obtained, when the learning rate is set to 0.001.

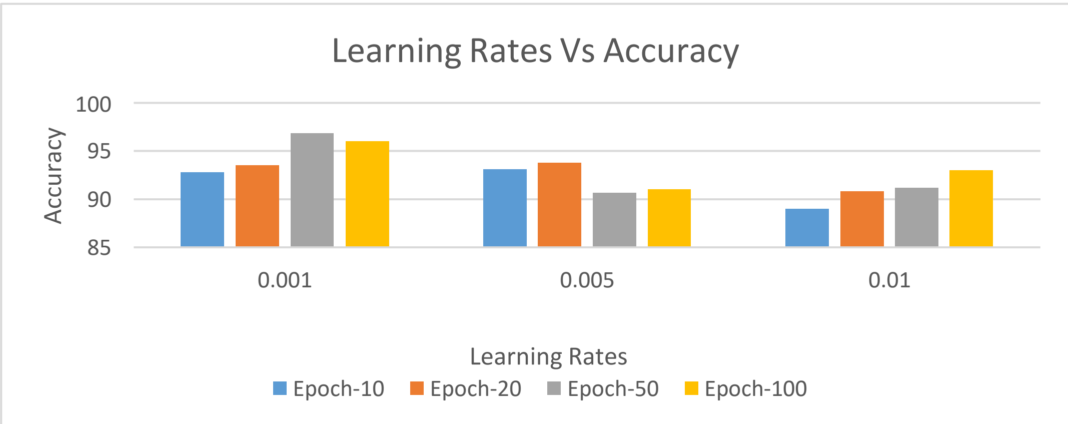

Fig. 8: Learning Rate versus Accuracy of proposed CNN model (based on split ratio of 70:30)

Figure 9 displayed a bar graph that compared the learning rate to the duration of the training time. In consideration of this splitting ratio, the three values for the learning rate are chosen as: 0.001, 0.005, and 0.01. The amount of time spent in training is directly proportional to the rate at which new information is absorbed, and the amount of time spent in training is shorter for learning rates and epochs of 0.001 and 10, correspondingly.

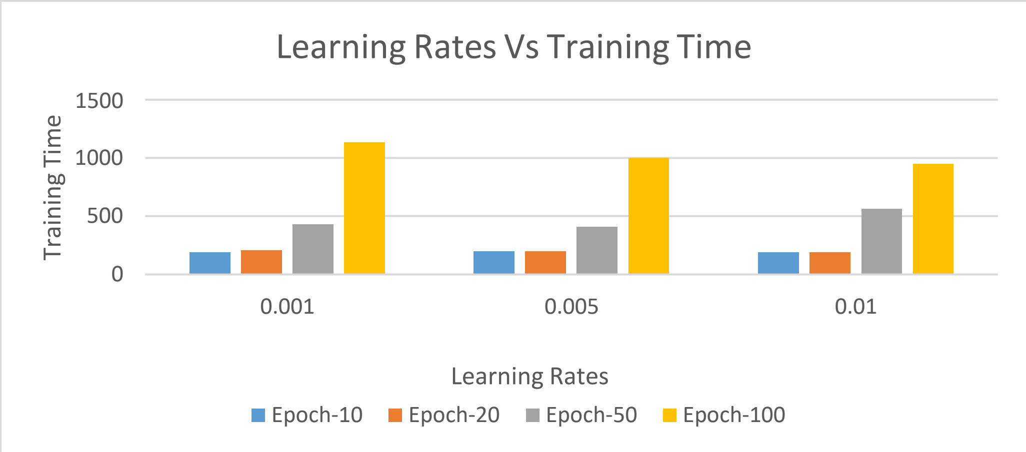

Fig. 9: Learning Rate verses Training Time of proposed CNN approach (depending on split ratio of 80:20)

The learning rate versus accuracy connection is depicted using a bar chart in Figure 10. The f our different epoch values were chosen depending on this split ratio: 10, 20, 50, and 100. The accuracy of the model will eventually suffer in proportion to the acceleration of its learning rate. The highest level of accuracy is achieved possible with a learning rate of 0.001, which is 97.86 %.

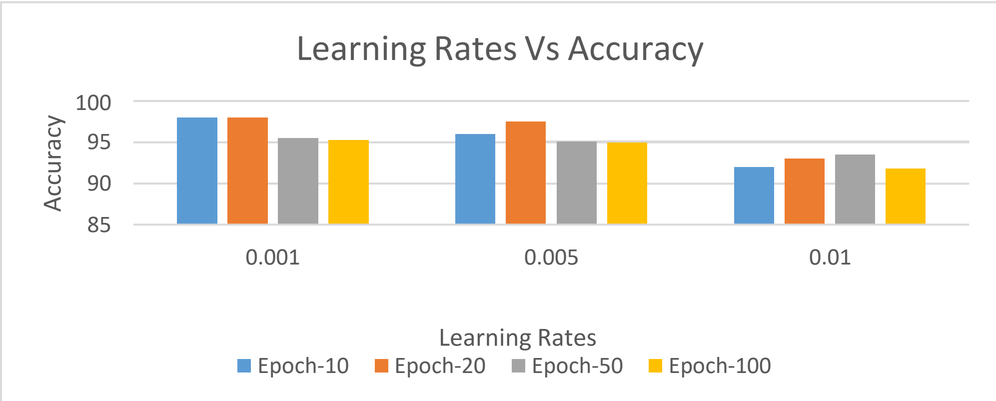

Fig. 10: Learning Rate versus Accuracy of proposed CNN model (depending on split ratio of 80:20)

When comparing the two desired performance from the suggested traditional ML as well as CNN models, it was found that the CNN models achieved a higher level of accuracy than ML. As a result of this observation, it is concluded that the 5-layer CNN approach yields the best results compared to the other distributions when it is trained with a learning rate of 0.001, an epoch of 10, and a training duration of 15 seconds. The accuracy of the 5-Layered CNN was calculated to be 97.86% when utilising an 80:20 split ratio.

5. Conclusion and Future Scope

The work that has been presented comprises an overview of the effectiveness of autonomous brain tumour detection from MR imaging and CT scans using fundamental image processing methodologies that depend on numerous hard and soft computing techniques. In addition, six traditional classifiers were utilised in order to locate the brain tumours in the images. After then, CNN was utilised for the purpose of identifying brain tumours in order to include deep learning approaches into the research work. The outcome of the conventional ML with the best accuracy method (Support Vector Machine) was analysed to the outcome of the conventional CNN. When the desired efficiency from the suggested traditional ML models and the CNN models were compared, it was discovered that the CNN models obtained a greater degree of accuracy than ML. As a result of this experimental finding, it is observed that the 5-layer CNN approach obtains the best outcome compared to the other distributions when it is trained with a learning rate of 0.001, an epoch of 10, and a training duration of 15 secs. The 5-Layered CNN has obtained a highest accuracy of 97.86% when utilising an 80:20 split ratio.

When examining the connection between stroke and brain tumours, standard approaches of investigation were not used. The preceding discussion makes it abundantly evident that the conventional system for the diagnosis of brain tumours and strokes lacks automated methods for the detection and segmentation of brain tumours as well as strokes. As a consequence of this, enhancing the accuracy of tumour and stroke segmentation for detection reasons is an absolute requirement. In addition, a magnetic resonance imaging (MRI) scan of the brain could be carried out in order to pinpoint the particular area of the brain that has been affected by the stroke.

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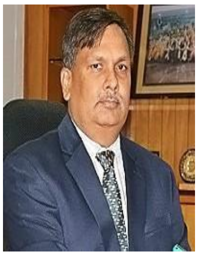

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