International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Deep Learning and Feature Extraction of Brain Tumour Detection

[1]Zahraa H. Ali, [2]Ali K. Al-Ali, [3]Noor M. Al-Moosawi

Submitted: 15/02/2023 **Revised:** 19/04/2023 **Accepted:** 10/05/2023

Abstract: In medical imaging, automated flaw detection has grown in importance. The ability to forecast tumor (brain) detection on one's own during an MRI scan is essential for preparing patients. Conventional methods of calculating z are developed to facilitate the work of radiologists. The size and variety of molecular structures in brain tumours presents a challenge for MRI diagnosis. This research uses deep learning (DL) techniques including support vector machines (SVM), artificial neural networks (ANN), and convolutional ANN to detect tumours in MRI scans (CNN). Segmentation scanning, feature extraction, and brain tumor classification are steps in the recommended technique. The second step consists of dataset preparation and input picture scanning. The third step involves figuring out how to extract features from a scanned picture. A number of machine learning methods are then utilized to classify the data according on these criteria. One of the most well-known neural networks (CNN) is employed in this article to differentiate between different kinds of MRI tumors.

Keywords*: Brain tumor, Image acquisition, Deep learning algorithm, MRI Imaging*

1. Introduction

Doctors will serve their patients with high-quality medical care in the age of e-healthcare & information technology [1]. This study examines the challenges surrounding the segmentation and treatment of defective normal tissues [2], [3], Grey matter (GM) operations, detection of white matter (WM), or regulation of cerebrospinal fluid (CSF) have been recovered from appropriate MR imaging methods and images using a vector support (SVM) classifier and the suitable feature extraction approaches [4]. Tumors form when cancer cells grow or divide out of control [5]. A brain tumour is an abnormal proliferation of diseased or malignant cells that cannot be controlled or kept in check. Brain tumours may be either benign growths or malignant ones [6]. The structural standardisation of benign brain tumours for patients includes the absence of active (cancerous) cells [6]. Malignant brain tumours in individuals are physically diverse (non-uniform) and include types of active cancer cells. Gliomas and meningiomas are examples of benign tumours, which are low-grade tumours and growths [7].

Malignant tumours, such as glioblastoma and astrocytoma, are characterised by rapid and uncontrolled cell proliferation [8]. The WHO and the American Brain Tumor Speculation Association (ABTA) both agree that the grade I and grade IV measures are the gold standard for distinguishing between benign and malignant tumours [9]. On this scale, grade I (classified) as well as grade II glioma development were reached by benign malignancies, whereas grade III and grade IV glioma development were reached by different types of malignant tumours.

Grade I and II cancers have a sluggish growth rate, but grade II tumours have a high growth rate[10]. Untreated, a low-grade brain tumour will progress to a high-grade tumour, and then to a malignant brain tumour, which is characterised by rapid, erratic development. Grade II glioma patients may be followed with scans such as MRI and CT scans on a regular basis (every six to twelve months) [11]. Brain tumours may afflict anybody at any age, and the consequences on the body differ from person to person. Malignant brain tumours of grades III and IV may be treated with radiation, chemotherapy, or a combination of the two techniques, whereas low-grade glioma (uncontrolled growth) benign tumours of grades I and II are considered curable with a comprehensive surgical surgery [12].

Malignant glioma refers to both type III and type IV gliomas, sometimes referred to as anaplastic astrocytoma. In contrast to most low-grade tumours, anaplastic astrocytomas are tumours of intermediate grade, characterised by a higher growth index and atypical features in their development [13]. Glioblastoma is the highest-grade glioma and the most dangerous kind of astrocytoma seen in patients. Necrosis (dead cells) and an unchecked proliferation of several blood artery types surrounding the tumour segment distinguish glioblastoma from other kinds of tumours [14].

1Collage of science ,Computer department ,University of Basrah ,Iraq
zahraa.ali@uobasrah.edu.iq
2Collage of science ,Geology department ,University of Basrah ,Iraq
ali.abbas@uobasrah.edu.iq
3Collage of Computer science and information technology , University of Basrah ,Iraq
almoosawinoor2@gmail.com

Glioblastoma at the grade IV tumour stage is an exceptionally uncontrolled kind of development that is very infectious and malignant. Segmentation is utilised to identify contaminated tumour tissues as compared to other tumour groups using various forms of medical imaging techniques [15]. The term "segmentation" refers to the process by which a single picture is broken down into smaller, more manageable pieces based on commonalities in colour, shape, size, orientation, texture, contrast, brightness, motion, borders, and even grayscale [16]. It's an essential part of the process of processing images. White matter (WM), grey matter (GM), as well as cerebrospinal fluid (CSF) development stages can be determined through the process of brain tumour segmentation, which involves separating as well as differentiating tumour tissue (such as oedema and dead cell formation) from healthy brain tissue and tumours using magnetic resonance images or even other imaging techniques (CSF) [17].

2. The Comprehensive Theoretical Basis

2.1. Detection and identification of brain tumors in MRI imaging

Reprocessing MRIs of the brain using a median filter allows for the evaluation of brain tissue by morphological segmentation and tumour extraction algorithms, which may then be used to diagnose brain cancer [15]. This technique for capturing a clear MRI of the tumour works well. Extraction of the tumour area from an MR image for the purposes of detection, determination, identification, and classification of brain tumours is described using a neuro-fuzzy classifier [18], After that, the grey level development and construction of co-occurrence method matrix procedure was used to compute features from the recovered texture (GLCM) Invasive tumours were detected using neural networks and segmentation algorithms [19]. The extraction of MRI functions and derived features is performed with the use of patient-controlled analgesia (PCA). And the greatest recognition rate is about 96.7 percent, with an average of 88.2 percent. Rajesh and coworkers suggested a segmentation method for identifying brain tumours on MRI scans using a probiotic neural network (PNN) [19]–[21]. The PNN urged caution when giving names to malignant brain tumors. Using a positron emission tomography (PET) scanner to take photographs of the brain, Suchita and Lalit developed an unsupervised learning technique [22]. To prepare the MRI images for analysis, we apply a threshold, filter out the background noise, and manually segment the tumour [23]. The GLCM technique, which is often used for image processing, development, determination, and subsequent self-organizing mapping, is applied and integrated in order to recognise and keep the brain's structure (SOM).

2.2. Brain tumour types

When cell division rates rise without corresponding neuronal death rates falling, the result is a tumour. The effects of a brain tumour may be devastating, affecting not just the brain but the whole body and even the skull. The incidence of brain tumours continues to rise at an alarming rate [21]. To improve treatment for brain cancer and other illnesses, early diagnosis is crucial. The early detection of brain tumours is another use of MRI technology. The patient is not given any drugs, the procedure causes no discomfort, and just a little quantity of radiation is used in an MRI. Axial, coronal, & sagittal pictures are taken in the typical MRI scanning order. By combining the information from its three different imaging modalities, MRI can provide more precise details on the tumor's anatomy, physiology, and extent [24]. There are three methods for carrying out a 3D MRI phase scan. These two forms of tumours may be indistinguishable on a single 3D brain MRI scan of biological tissue. T1- and T2-weighted sequences are what make up MR imaging. The T1-weighted MRI may help find brain tumours that have metastasized to the CSF spaces of the spinal column and brain. T2-weighted magnetic resonance imaging uses strong contrast to show disease on the other side of the image. Cancerous growths in the brain are a possibility nearby. As a result, tumours are given names that identify the cellular origins of the disease. Brain and pituitary gland tumours are rather common. As its name implies, glioma is a disorder of the brain and spinal cord. The glial cells of the brain are the source of gliomas. It's a tumour of the brain that begins in the protective layer around the brain called the dura.This is one of the most common types of brain tumours in adults. consists of between 15 and 20 percent of brain tumours [21]. Eventually, a tumour forms on the pituitary gland, reestablishing hormonal equilibrium and controlling the functioning of other glands, including those responsible for the menstrual cycle. Misdiagnosis and wasted time occur when T1-weighted MRI is used to classify brain tumours into three categories [25]. Modern MR diagnostic software already makes use of deep learning (DL) and image recognition algorithms to speed up the process and lower the margin of error. Artificial intelligence refers to a subset of machine learning that uses a deep learning-based technique for object recognition using multilayered neural networks. As with ML algorithms, DL may make use of visual, auditory, and textual inputs to inform its analyses [24], However, they are notably distinct methods to solve the issue. In this study, we want to develop a web-based tool that can use DL to classify glioma, meningioma, and pituitary adnexa from a detailed T1 MRI image. It is believed that health practitioners and scientists may now quickly identify brain tumours due to the availability of free web-based diagnostic tools. Classifying brain tumours

may frequently benefit from using this website as a diagnostic tool (i.e., glioma, meningioma, pituitary). The results of the tests demonstrate that all of the indicators have a success rate of above 98% when used on the training dataset to differentiate between the various types of brain tumours. Except for sensitivity and the meningioma-specific MCC, all markers scored at or above 91%. The convolutional neural network (CNN) based model correctly recognises the various forms of brain tumours throughout both the training and evaluation phases [26], [27]. An fascinating CNN thesis investigates brain tumour classifications using public MRI data, grouping approximately 3,400 distinct T1-weighted images of the same people into 233 and 3,000 separate models using the DL approach. When applied to two distinct datasets, the developed approach achieves an overall accuracy of 96.13 and 98.7 percent.

2.3. Method for detection

A study of empirical studies indicates that automated brain tumour identification is crucial when human life is at danger [21], [28]. Method for identifying brain cancers, beginning with picture capture, preprocessing, extraction, and segmentation, is shown in Figure 1. Using a machine learning algorithm, the approach of function extraction and classification is often used to diagnose cancer from MRI images.

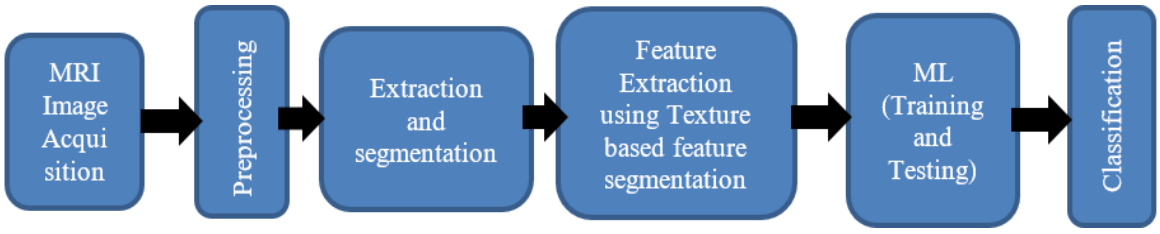

Fig 1. Usable method for brain tumor detection in MRI imaging

2.3.1. Image acquisition stage for MRI

In the first phase, MRI pictures for brain scanning are collected, which also serves as the input for the entire system's preprocessing phase [22]. In this phase, several types of picture samples are gathered for relevance evaluation. During the image capture and development phase, performance metrics are managed accordingly [29]. In Figure 2, the normal brain MR picture refers to scans devoid of tumors.

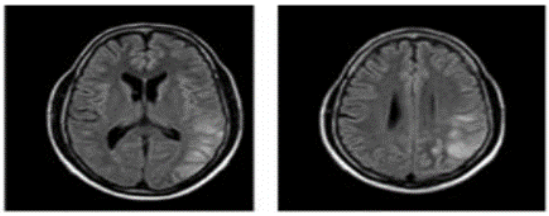

Fig. 2. Brain MR image (samples)

2.3.2. Pre-processing

When an image is preprocessed, it has an advantage by having some of its functionality refined before being processed further [24]. The following measures are performed as a precaution until the MRI pictures have been processed: Grayscale conversion and median filtering of the original red, green, & blue (RGB) MRI image are shown in Figure 3 (a) (b). Due to the requirement for more accurate analysis, the noise has been filtered away. Method for accurate edge identification and detection as demonstrated in Figure 3 (c). For image segmentation, the edge-detected image is required.. Figure 3 depicts the approach used to determine the location of the tumour in the watershed segmentation of the brain. Figure 4 (d). An picture is cut up into smaller pieces, or "segments." The purpose of segmentation is to reorganise representation visually[24]. The values of the objects and tools will vary on the same scale; for example, all pixels in the first object will have a value of 1, all pixels in the second object will have a value of 1, and all pixels in the third object and beyond will have a value of 2 [30], and so forth Figure 3 depicts several preprocessing approaches used to MR images of the brain.

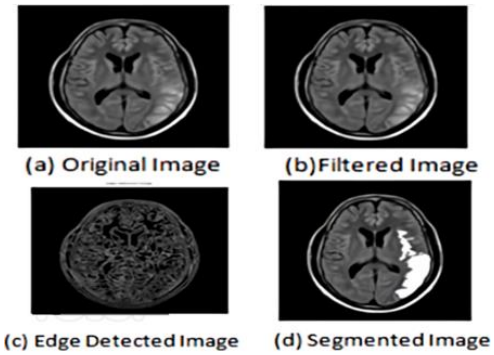

Fig. 3. Steps in getting MRI images ready for use (a) the original image, (b) the filtered image, (c) the edge-detected image, and (d) the segmented image.

2.3.3. Feature extraction

The process by which an algorithm takes massive amounts of data and reduces it to a more manageable set of operations is called "reduction to a function vector." [31]. During feature extraction, input data is turned into a set of functions. In magnetic resonance imaging (MRI), texture segmentation is a method used to provide a visual representation of the textures contained in the picture [32]. The GLCM method is a flexible, very effective instrument for eliminating certain traits [33]. Since the GLCM tools for texture extraction utilise fewer grey levels while improving overall categorization, they are extremely competent and are used in the development and identification procedure [34]. The grey level measurement and co-occurrence (GLC) attributes are utilised to further identify and discriminate between normal and aberrant behaviour [35]. There are texture-based details on the placement of things on the floor. Grey-tone spatial characteristics have a broader importance for image categorization.

2.3.4. Classification

Pattern recognition in brain images is sometimes performed using the multi-layer perceptron (MLP) and naive bayes (NB) algorithms [36] aiding in their education and development so that they may make wiser decisions Create an artificial neural network as part of this strategy (ANN) [37] Multiple inputs are translated into a single output variable, which is then fed into a second layer, and maybe even further layers, in order to get the desired result. Unique activation mechanisms govern the activity of each neuron in the MLP [29]. A feedforward circuit is characterised as a feedback circuit because it lacks feedback [36]. All relevant information may be found in the journal. When goals and results are in sync, learning happens via tweaks to the association weights [38]. Due of this unfavourable response, [39] The system is called "backward pathogenesis" as a joke. As a goal, the total weight values need to go down so that each edge has less chance of making a mistake. Figure 4 shows the results of all the steps mentioned, including the preprocessed image result (Figure 4a), the k-means segmented image result (Figure 4b), the fuzzy c-means segmented image result (Figure 4c), the clear border result (Figure 4d), and the feature extracted image result (Figure 4e) (e).

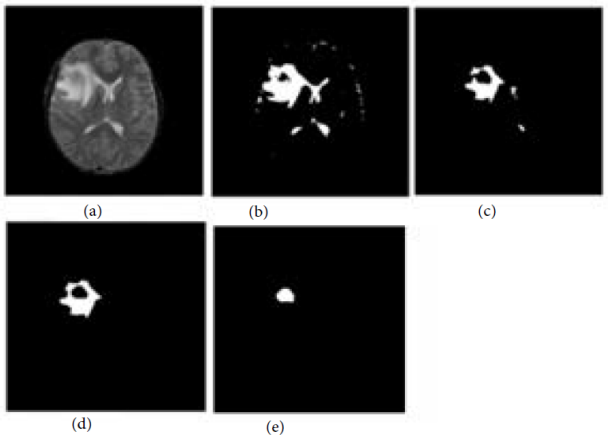

Fig. 4. Different MRI outputs, including the original picture (a), the k-means segmented image (b), and the fuzzy inference version (c), are classified. the c-means segmented picture, the clear border image, and the feature extracted image

To help highlight some of the comparing features, Table 1 shows the details of a comparison of different research work in the domain of the machine learning approach for recognising brain tumours. Multiple research projects' findings form the basis of the analysis. Table 1 displays a comparison of several articles by detecting method.

Table 1. Comparison among the research works

Authors	Findings
Kaur and Gujral [12]	This paper suggests and shows how to use machine learning techniques to help find brain tumours. In addition to the information that is gathered, the data collection can be made more accurate and detailed by taking into account all of the texture and force properties. The GLCM explains what the ideas are. The skin of this suggested work has life, visual contrast, dignity, and consistency. The Bayesian process gives a classification and accuracy rating of 97.6%, while the multi-layer peron grouping, distinction, as well as machine learning approaches aim for the top 2.2% of discrimination and accuracy for videos. (accuracy goal).
Bahadure, *et al.* [13]	In this study, the creative wave transformation (BWT) was used to speed up segmentation and make it easier. MR imaging is a useful tool for finding and dividing tumours for surgery or therapy, but this is a difficult and time-consuming process that radiologists cannot help with. So, using computer-aided technology is a must if you want to get past these problems. From each segmented tissue, SVM-dependent characteristics are extracted to increase classification accuracy and efficiency. On the basis of the technique's precision, sensitivity, specificity, and dice coefficients, its effectiveness and dependability for brain imaging research have been thoroughly tested. They demonstrated that the proposed technique successfully distinguished between images of healthy and diseased tissue with a 96.51 percent accuracy, a 94.2 percent sensitivity, as well as a 97.72 percent accuracy. The overall dice coefficient for these findings was 0.82.The computer-extracted tumour region overlapped more with the manually-made tumour region. Compared to the current state-of-the-art techniques, the findings emphasise accuracy and precision as important criteria.
Nadeem, *et al.* [14]	Recently, with the advent of DL, the fields of bioinformatics, medical image interpretation, and image recognition have all seen a renaissance. As a result, DL has had a major effect on the diagnosis and staging of cancers affecting a variety of organs, including the brain, liver, abdomen, and retina. We hope it will shed light on some of the fundamental concepts of DL and be useful in the fight against brain tumours (e.g., segmentation, classification, prediction, evaluation.). DL is used to handle the data layers of computational models, often integrating many levels of abstraction. Significant developments in the field of study are summarised in this article (i.e., DL in brain tumour analysis). Many distinct sorts of locations have been studied and evaluated, and a consistent taxonomy has emerged from these efforts.. Following is a topical examination of DL's primary shortcomings in the current technological environment, as well as a set of techniques for enhancing its use in the new media industry.
Gore and Deshpande [15]	Recently, DL has been crucial in reviving the fields of bioinformatics, medical image identification, and medical image interpretation. As a result, DL has had a substantial effect on the identification and quantification of malignancies in various organs and tissues, including brain tumours, the liver, the abdomen, and the retina. We hope that it will shed light on some of the foundational concepts of DL, since it is of great importance to the study of brain tumours (e.g., segmentation, classification, prediction, evaluation.).DL is used to handle the data layers of computational models, often integrating many abstraction levels. This article presents an overview of some of the most significant advancements in the subject of research (i.e., DL in brain tumour analysis). Various sorts of areas have been studied and assessed, and a consistent taxonomy has been maintained in the literature. The following is a topical analysis of the main problems with DL in the present technological setting, followed by a collection of methods for improving its use in the media sector.

3. Method

In this research, the authors used the segmentation and extraction of brain tumour features shown in Figure 5. Preprocessing, Image Segmentation Process, Morphological Image Processing Including (Dilation, Erosion), Brain Tumor Feature Extraction Including (Shape Feature, Shape Feature, Texture, Haar Wavelet Transform, Moment Invariants, Co-occurrence Matrix, Contrast, Homogeneity, Entropy, Energy, Correlation, Color Moments, and Intensity Features), and

Classification Methods) are the steps involved in the procedure.

A brief process was developed to generate a data set. For each shape's findings, static features and textural features are retrieved and recorded in a Microsoft Excel spreadsheet. Consequently, a collection of 22 traits is compiled and regarded an input to categorization algorithms.

A new data vector, dubbed Feature Vector, is generated once key features are extracted from MRI scans of brain tumors. Following this, a device or technique called a Classifier is used to turn the feature vector into a collection of classifications[33]. Using a standardized process, classification methodologies create classification models from raw data. Alternative classification strategies for Brain Tumors will be the focus of this study, including deep learning, artificial neural networks (ANN), and support vector machines (SVM). In each method, a learning algorithm is used to construct a model that accurately captures the association between the feature set and the class label in the input data. The method used by the classification algorithm is shown in Figure 7.

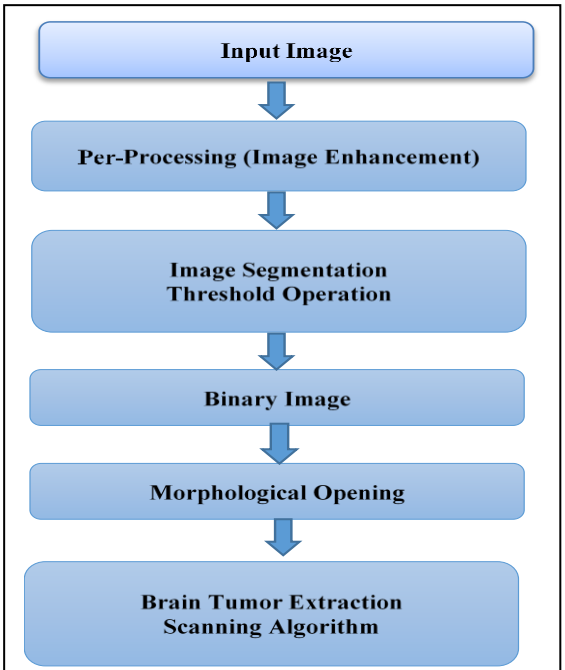

Fig. 5 Flowchart of segmenting brain tumor.

3.1. Neural Network

Authors employed back propagation neural networks (BPNN) to identify and categorize WBC into its five groups using our recommended technique. Biological neural networks are categorized and imitated by computational models of artificial neural networks. BPNN use needs training.

The features vector has a total of twenty-two input characteristics. The vector is populated with the MRI image characteristics that are judged significant for its representation. By transforming the characteristics vector into a collection of classes, neural networks are then employed to tackle the Brain tumour classification issue. In this technique, a learning algorithm is used to choose a model that best captures the connection between the features and the classes in the input data. Here we are at the Input Stage. The size of the input features controls the number of neurons in the input layer. In this instance, the author evaluated the 22 retrieved characteristics for each. Set the number of neurons to 32, 64, 128 and three levels of hidden neurons. The authors used 80% of the data for training purposes and 20% for testing and validation. Quantity of training periods (100). Due to network time, this connection should be ended early. Debug is set to true so the classifier may send more information to the console. Weight update learning rate = 0.00001 for the learning rate. shuffle=True, the number of hidden layers consists of three levels for random data distribution, VERBOSE 1. Figure 8 depicts the architecture of the ANN used in this work.

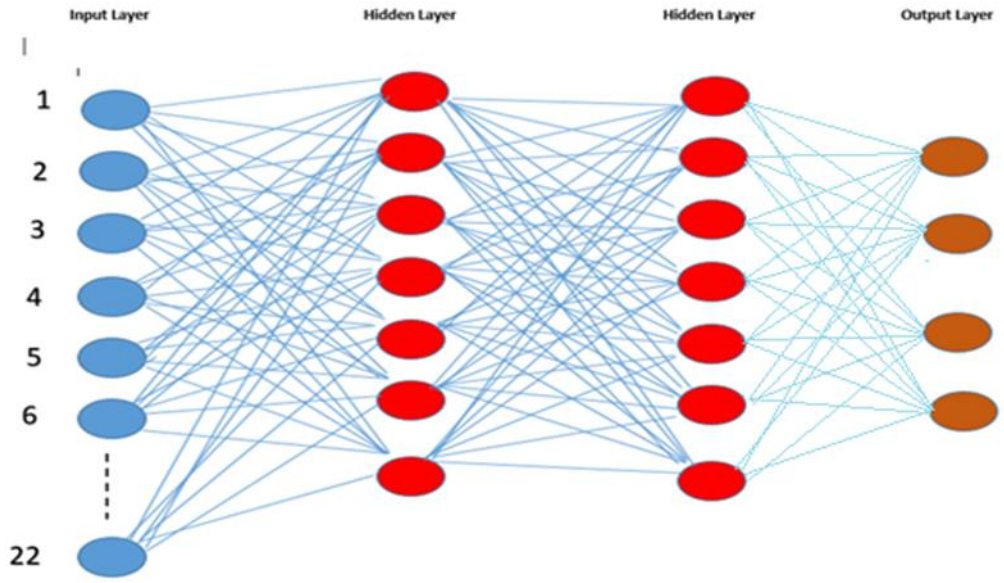

Fig. 8 ANN feature extraction for MRI brain tumor

3.2. Support Vector Machine

A machine learning approach called the Support Vector Machine is predicated on the notion of structural risk reduction and convex optimization. Its primary purpose is to overcome concerns with binary categorization. The objective is to develop a hyperplane that best differentiates the classes. It is often denoted in the classification by class labels such as "-1" and "+1."

The author utilize a support vector machine classifier to separate Brain tumor pictures pixels into four sub-categories based on wavelet coefficients. This approach is efficient at modelling a wide variety of data sources and is resistant to non-linear classification in high-dimensional space.

The author has used datasets with training and testing subcategories extracted from Features. The significant characteristics for each picture depicting brain tumor cells provided to the classifier are 22 attributes. That example, the input number for the classifier is 22 feature. feature vector identified as class-specific, is identifying the huge margin hyperplane, where the decision boundary is also effectively influenced by kernel settings. SVM-Type: C=1, Classification; SVM-Kernel: liner; kernel function type: Gaussian; Sigma: 0.11; gamma:0.5; filter Type: 'normalize learn data'; debug: true.

3.3. Convolution Neural Network (CNN)

The artificial neuron takes in data and outputs a single signal, which may be shared with neighbouring artificial neurons. A feature value from an external information sample, like as an article or an image, or the results of other neurons, may be used as inputs. The task, such as object recognition from a photograph, is completed by a neural network's last set of output neurons. Bias is applied to the weighted sum of inputs before the neuron's output is computed. The activation refers to this aggregated weighting.

The 1D CNN model consists of 19 layers, four of which are convolutional layers, two with a 0.5 percent dropout, and two fully connected layers. Model parameters, such as the number of convolutional layers, filters, as well as epochs, are improved using cross-validation approaches. The CNN layers and their respective descriptions are shown in Table 2. The spatial and local feature map may be retrieved effectively utilising the CNN model's thirteenth layer, which consists of 10 convolutional filters. In an ECG signal, the filters can distinguish edges, vertical and horizontal lines, and other features.

Table 2. Explanation models 1D CNN		
No. of Layers	**Names**	**Explanation**
1	Inputs	Depends on the input with 'zerocenter' normalization.
2	Layer1 Convolution	20 7*7 convolutions layers with (1 *1) paddings same
3	Batch normalization 1	Batch normalization1
4	ReLU, Clipped	ReLU is clipped ceilings5
5	Drop Out	Drop Out 50%
6	Layer2 Convolutions	20 convolutions of 9*9 using length (1 * 1) and padding same.
7	Batch normalization 2	Batch normalization 2
8	ReLU Leaky	ReLU with a leaky scale of 0.01
9	Layer3 Convolution	30 5x5 convolution layer with (1 * 1) stride and padding 'same'
10	Batch normalization 3	Batch normalization 3
11	Soft Max	Soft Max
12	Drop out	Drop out 50%
13	Layer4 Convolution	10 3x3 convolution layer with 1 * 1 stride and padding 'same'.
14	Batch normalization 4	Batch normalization 4
15	ReLU	ReLU
16	Completely Connected 1	60 layers are totally connected.
17	Completely Connected 2	Two layers that are completely interconnected
18	Soft Max	The last Fully Connected layer's activation function.
19	Classifications	Entropy of the output Entropy the output

4. Results and Discussion

A tumour is formed when abnormal cells proliferate inside the brain. Tumors may be classed as either cancerous (malignant) or benign. Primary brain tumours are those that originate inside the brain, while secondary brain tumours, or brain metastasis tumours, have spread from elsewhere. Depending on where portion of the brain is affected, all forms of brain tumours may induce a range of symptoms. These symptoms include headaches, seizures, eye difficulties, nausea, and mental abnormalities. A headache often improves in the morning and fades after vomiting. Other indicators may include problems speaking, walking, or feeling things. As the disease develops, unconsciousness may develop.

There are several datasets, but the authors gather photos from datasets including : (figshare, SARTAJ, datasetBr35H). The authors gathered 6000 photos and allocated 80% of the acquired data for training and 20% for validation and testing. This dataset comprises 6000 pictures of human brain MRI scans that have been categorized into four classes: glioma - meningioma - no tumors and pituitary. No photos of tumor classes were extracted from the Br35H dataset.

As previously stated, the author employed datasets with 22 characteristics per picture for the research. These characteristics were then converted into a database. There are databases for the images we have collected. After supplying all characteristics to the classifiers, we evaluated their performance and accuracy to determine which classifier performed the best overall. We used four classifier algorithms, each of which functioned independently, to accomplish this. Following feature extraction, these characteristics were submitted as input to the classifier method for the 6000-photo standard dataset. These four types of MRI brain tumours that we have categorised using these classifier methods are all basic and easy to understand. As data, it provides to the classifier the extracted characteristics from the datasets. The outcomes of the suggested strategies are shown in tables 3 and 4.

Table 3 : Comparison between testing , training , validation for all methods

Dataset type	Testing	Training	Validation
SVM	97.35%	98.71%	97.89%
ANN	98.52%	98.8%	98.26%
CNN	99.18%	99.75%	99.12%

Table 4 Accuracy of the approach methods in MRI brain tumor

Model	Accuracy	No. of Epoch	Training Time for 1 Epoch
CNN	**99.26**	**50 Epoch**	**13 sec.**
SVM	**97.91**	**150 Epoch**	**12 sec.**
ANN	**98.55**	**100 Epoch**	**21 sec.**

5. Conclusion

The MRI imaging methods used to distinguish between benign and malignant growths have become an integral part of the patients' treatment regimens. Thus, medical practitioners may assess the amount of strategic considerations necessary to comprehend the procedures and considerations required for treatment processes. In this study, numerous features of MRI imaging methods are described in order to examine the research findings. In addition, a quick comparative literature study was undertaken to assess the results. Deep learning techniques, which depend on conceptual models with numerous layers of abstraction to cope with enormous volumes of data, have many applications in the medical imaging, processing, research, as well as bioinformatics fields. The incidence of DL has increased dramatically. The diagnostic and inferential environment in healthcare is only one of several that have found deep learning & neural networks to be transformative. These advances have had far-reaching consequences for many different types of pathology, such as liver disease, esophageal illness, brain tumours, as well as retinal disease. The primary objective of this work is to analyse the present applications of DL in the field of brain tumour research (e.g., segmentation, classification, prediction, evaluation).This publication (proposed DL in analysis of brain tumours) offers a number of scientific contributions to the field.

References

[1] M. S. Goswami and M. L. K. P. Bhaiya, “Brain tumour detection using unsupervised learning based

neural network," in *Proceedings - 2013 International Conference on Communication Systems and Network Technologies, CSNT 2013*, Apr. 2013, pp. 573–577. doi: 10.1109/CSNT.2013.123.

[2] T. Rajesh and R. S. M. Malar, "Rough set theory and feed forward neural network based brain tumor detection in magnetic resonance images," in *International Conference on Advanced Nanomaterials & Emerging Engineering Technologies*, Jul. 2013, pp. 240–244. doi: 10.1109/ICANMEET.2013.6609287.

[3] S. Rajeshwari and T. S. Sharmila, "Efficient quality analysis of MRI image using preprocessing techniques," in *2013 IEEE Conference on Information and Communication Technologies, ICT 2013*, Apr. 2013, pp. 391–396. doi: 10.1109/CICT.2013.6558127.

[4] T. A. Assegie, R. L. Tulasi, and N. K. Kumar, "Breast cancer prediction model with decision tree and adaptive boosting," *IAES International Journal of Artificial Intelligence (IJ-AI)*, vol. 10, no. 1, pp. 184–190, Mar. 2021, doi: 10.11591/ijai.v10.i1.pp184-190.

[5] D. Singh and K. Kaur, "Classification of abnormalities in brain MRI images using GLCM , PCA and SVM," *International Journal of Engineering and Advanced Technology (IJEAT)*, vol. 1, no. 6, pp. 243–248, 2012.

[6] P. Gadpayleand and P. S. Mahajani, "Detection and classification of brain tumor in MRI images," *International Journal of Emerging Trends in Electrical and Electronics (IJETEE)*, vol. 5, no. 1, 2013.

[7] M. Shasidhar, V. S. Raja, and B. V. Kumar, "MRI brain image segmentation using modified fuzzy c-means clustering algorithm," in *Proceedings - 2011 International Conference on Communication Systems and Network Technologies, CSNT 2011*, Jun. 2011, pp. 473–478. doi: 10.1109/CSNT.2011.102.

[8] K. Sharma and N. Kaur, "Comparative analysis of various edge detection techniques," *International Journal of Advanced Research in Computer Science and Software Engineering*, vol. 3, no. 12, pp. 617 – 621, 2013.

[9] J. Selvakumar, A. Lakshmi, and T. Arivoli, "Brain tumor segmentation and its area calculation in brain MR images using K-mean clustering and Fuzzy C-mean algorithm," in *IEEE-International Conference on Advances in Engineering, Science and Management, ICAESM-2012*, 2012, pp. 186–190. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/6215996/ metrics#metrics

[10] R. J. Ramteke and K. M. Yashawant, "Automatic medical image classification and abnormality detection using k-nearest neighbour," *International Journal of Advanced Computer Research*, vol. 2, no. 4, pp. 190–196, 2012, [Online]. Available: https://www.researchgate.net/publication/305403850_Automatic_Medical_Image_Classification_and_Abnormality_Detection_Using_K-_Nearest_Neighbour

[11] X. Xuan and Q. Liao, "Statistical structure analysis in MRI brain tumor segmentation," in *Proceedings of the 4th International Conference on Image and Graphics, ICIG 2007*, Aug. 2007, pp. 421–426. doi: 10.1109/ICIG.2007.181.

[12] K. Sharma, A. Kaur, and S. Gujral, "Brain tumor detection based on machine learning algorithms," *International Journal of Computer Applications*, vol. 103, no. 1, pp. 7–11, Oct. 2014, doi: 10.5120/18036-6883.

[13] N. B. Bahadure, A. K. Ray, and H. P. Thethi, "Image analysis for MRI based brain tumor detection and feature extraction using biologically inspired BWT and SVM," *International Journal of Biomedical Imaging*, pp. 1–12, 2017, doi: 10.1155/2017/9749108.

[14] M. W. Nadeem *et al.*, "Brain tumor analysis empowered with deep learning: A review, taxonomy, and future challenges," *Brain Sciences*, vol. 10, no. 2, pp. 1–33, Feb. 2020, doi: 10.3390/brainsci10020118.

[15] D. V. Gore and V. Deshpande, "Comparative study of various techniques using deep learning for brain tumor detection," in *2020 International Conference for Emerging Technology (INCET)*, Jun. 2020, pp. 1–4. doi: 10.1109/INCET49848.2020.9154030.

[16] W. Widhiarso, Y. Yohannes, and C. Prakarsah, "Brain tumor classification using gray level co-occurrence matrix and convolutional neural network," *IJEIS (Indonesian Journal of Electronics and Instrumentation Systems)*, vol. 8, no. 2, pp. 179–190, Oct. 2018, doi: 10.22146/ijeis.34713.

[17] H. Mohsen, E.-S. A. El-Dahshan, E.-S. M. El-Horbaty, and A.-B. M. Salem, "Classification using deep learning neural networks for brain tumors," *Future Computing and Informatics Journal*, vol. 3, no. 1, pp. 68–71, Jun. 2018, doi: 10.1016/j.fcij.2017.12.001.

[18] K. Kamnitsas *et al.*, "Efficient multi-scale 3D CNN

with fully connected CRF for accurate brain lesion segmentation," *Medical Image Analysis*, vol. 36, pp. 61–78, Feb. 2017, doi: 10.1016/j.media.2016.10.004.

[19] S. K. Chandra and M. K. Bajpai, "Effective algorithm for benign brain tumor detection using fractional calculus," in *TENCON 2018 - 2018 IEEE Region 10 Conference*, Oct. 2018, pp. 2408–2413. doi: 10.1109/TENCON.2018.8650163.

[20] S. W. Kareem, R. Z. Yousif, and S. M. J. Abdalwahid, "An approach for enhancing data confidentiality in hadoop," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 20, no. 3, pp. 1547–1555, Dec. 2020, doi: 10.11591/ijeecs.v20.i3.pp1547-1555.

[21] A. Triayudi and I. Fitri, "Comparison of the feature selection algorithm in educational data mining," *TELKOMNIKA (Telecommunication Computing Electronics and Control)*, vol. 19, no. 6, pp. 1865–1871, Dec. 2021, doi: 10.12928/telkomnika.v19i6.21594.

[22] J. Seetha and S. S. Raja, "Brain tumor classification using Convolutional Neural Networks," *Biomedical and Pharmacology Journal*, vol. 11, no. 3, pp. 1457–1461, Sep. 2018, doi: 10.13005/bpj/1511.

[23] J. Cheng *et al.*, "Enhanced performance of brain tumor classification via tumor region augmentation and partition," *PLoS ONE*, vol. 10, no. 10, pp. 1–13, Oct. 2015, doi: 10.1371/journal.pone.0140381.

[24] G. S. Tandel *et al.*, "A review on a deep learning perspective in brain cancer classification," *Cancers*, vol. 11, no. 1, pp. 1–32, Jan. 2019, doi: 10.3390/cancers11010111.

[25] G. Litjens *et al.*, "A survey on deep learning in medical image analysis," *Medical Image Analysis*, vol. 42, pp. 60–88, Dec. 2017, doi: 10.1016/j.media.2017.07.005.

[26] L. Szilagyi, L. Lefkovits, and B. Benyo, "Automatic brain tumor segmentation in multispectral MRI volumes using a fuzzy c-means cascade algorithm," in *2015 12th International Conference on Fuzzy Systems and Knowledge Discovery (FSKD)*, Aug. 2015, pp. 285–291. doi: 10.1109/FSKD.2015.7381955.

[27] M. Soltaninejad *et al.*, "Automated brain tumour detection and segmentation using superpixel-based extremely randomized trees in FLAIR MRI," *International Journal of Computer Assisted Radiology and Surgery*, vol. 12, no. 2, pp. 183–203, Feb. 2017, doi: 10.1007/s11548-016-1483-3.

[28] J. R. Fink, M. Muzi, M. Peck, and K. A. Krohn, "Continuing education: Multi-modality brain tumor imaging – MRI, PET, and PET/MRI," *Journal of Nuclear Medicine*, vol. 56, no. 10, pp. 1554–1561, Oct. 2015, doi: 10.2967/jnumed.113.131516.

[29] G. M. Shivakumarswamy, P. V Akshay, T. A. Chethan, B. H. Prajwal, and S. V Hande, "Brain tumour detection using Image processing and sending tumour information over GSM," *International Journal of Advanced Research in Computer and Communication Engineering*, vol. 5, no. 5, pp. 179–183, 2016, doi: 10.17148/IJARCCE.2016.5543.

[30] Y. Jia, Y. Zhang, and T. Rabczuk, "A novel dynamic multilevel technique for image registration," *Computers & Mathematics with Applications*, vol. 69, no. 9, pp. 909–925, May 2015, doi: 10.1016/j.camwa.2015.02.010.

[31] T. Kalaiselvi, P. Nagaraja, and P. Sriramakrishnan, "A simple image processing approach to abnormal slices detection from MRI tumor volumes," *The International journal of Multimedia & Its Applications*, vol. 8, no. 1, pp. 55–64, Feb. 2016, doi: 10.5121/ijma.2016.8105.

[32] R. Kumar and K. J. Mathai, "Brain tumor segmentation by modified k-mean with morphological operations," *International Journal of Innovative Research in Science, Engineering and Technology*, vol. 6, no. 8, pp. 16191–16198, 2017, doi: 10.15680/IJIRSET.2016.0608079.

[33] A. Mukaram, C. Murthy, and M. Z. Kurian, "An automatic brain tumour detection, segmentation and classification using MRI image," *International Journal of Electronics, Electrical and Computational System*, vol. 6, no. 5, pp. 54–65, 2017, [Online]. Available: https://www.semanticscholar.org/paper/An-Automatic-Brain-Tumour-Detection%2C-Segmentation-Mukaram-Murthy/92e91674497afffd2acca94d42ac39513e10e184

[34] S. Patel and D. Rao, "Brain tumor detection in MRI images with new multiple thresholding," *Journal of Network Communications and Emerging Technologies (JNCET)*, vol. 7, no. 6, pp. 34–39, 2017, [Online]. Available: https://www.jncet.org/Manuscripts/Volume-7/Issue-6/Vol-7-issue-6-M-08.pdf

[35] A. Pawar *et al.*, "Adaptive FEM-based nonrigid image registration using truncated hierarchical B-splines," *Computers & Mathematics with Applications*, vol. 72, no. 8, pp. 2028–2040, Oct. 2016, doi: 10.1016/j.camwa.2016.05.020.

[36] R. Sharmila and K. S. Joseph, "Brain tumour detection of MR image using Naïve Beyer classifier and support vector machine," *nternational Journal of Scientific Research in Computer Science, Engineering and Information Technology*, vol. 3, no. 3, pp. 690–695, 2018, [Online]. Available: https://1library.net/document/zp2wwroy-brain-tumour-detection-naive-classifier-support-vector-machin.html

[37] M. Havaei, F. Dutil, C. Pal, H. Larochelle, and P.-M. Jodoin, "A convolutional neural network approach to brain lesion segmentation," in *Brainlesion: Glioma, Multiple Sclerosis, Stroke and Traumatic Brain Injuries*, Chsm: Springer International Publishing, 2016, pp. 195–208. doi: 10.1007/978-3-319-30858-6_17.

[38] S. Pereira, A. Pinto, V. Alves, and C. A. Silva, "Deep convolutional neural networks for the segmentation of gliomas in multi-sequence MRI," in *Brainlesion: Glioma, Multiple Sclerosis, Stroke and Traumatic Brain Injuries*, Chsm: Springer International Publishing, 2016, pp. 131–143. doi: 10.1007/978-3-319-30858-6_12.

[39] Kamnitsas, K.; Ledig, C.; Newcombe, V.F.; Simpson, J.P.; Kane, A.D.; Menon, D.K.; Glocker, B. Efficient multi-scale 3D CNN with fully connected CRF for accurate brain lesion segmentation. Med. Image Anal. 2017, 36, 61–78. [CrossRef]

[40] D. Yi, M. Zhou, Z. Chen, and O. Gevaert, "3-D convolutional neural networks for glioblastoma segmentation," pp. 1–8, Nov. 2016, [Online]. Available: http://arxiv.org/abs/1611.04534

[41] O. H. Salman, M. F. A. Rasid, M. I. Saripan, and S. K. Subramaniam, "Multi-sources data fusion framework for remote triage prioritization in telehealth," *Journal of Medical Systems*, vol. 38, no. 9, pp. 1–23, Sep. 2014, doi: 10.1007/s10916-014-0103-4.

[42] S. M. R. K. Al-Jumur, S. W. Kareem, and R. Z. Yousif, "Predicting temperature of Erbil City applying deep learning and neural network," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 22, no. 2, pp. 944–952, May 2021, doi: 10.11591/ijeecs.v22.i2.pp944-952.

[43] S. Kareem and M. C. Okur, "Bayesian network structure learning using hybrid bee optimization and greedy search," in *3rd International Mediterranean Science and Engineering Congress (IMSEC 2018)*, 2018, pp. 1–7. [Online]. Available: https://www.researchgate.net/profile/Shahab-Kareem/publication/333320417_Bayesian_network_structure_learning_using_hybrid_bee_optimization_and_greedy_search/links/5ce6aaf9458515712ebc96da/Bayesian-network-structure-learning-using-hybrid-bee-optimization-and-greedy-search.pdf

[44] S. W. Kareem and M. C. Okur, "Pigeon inspired optimization of bayesian network structure learning and a comparative evaluation," *Journal of Cognitive Science*, vol. 20, no. 4, pp. 535–552, Dec. 2019, doi: 10.17791/jcs.2019.20.4.535.

[45] S. W. Kareem and M. C. Okur, "Bayesian network structure learning based on pigeon inspired optimization," *International Journal of Advanced Trends in Computer Science and Engineering*, vol. 8, no. 1, pp. 131–137, 2019, doi: 10.30534/ijatcse/2019/2281.22019.

[46] S. W. Kareem and M. C. Okur, "Evaluation of bayesian network structure learning using elephant swarm water search algorithm," in *Handbook of Research on Advancements of Swarm Intelligence Algorithms for Solving Real-World Problems*, Hershey: IGI Global, 2020, pp. 139–159. doi: 10.4018/978-1-7998-3222-5.ch008.