# DESIGN A COMPUTER-AIDED DIAGNOSIS SYSTEM FOR BRAIN TUMOR CLASSIFICATION USING CNN

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**ABSTRACT:**
Around the world, brain tumour is one of the major threat confronted by many people. Additionally, a brain tumour develops when abnormal cells grow inside the brain and is one of the most deadly disease to affect human survival. Though, it has some limitations, the classification of the brain tumour by the CAD system provide an magnificent outcome. For rapid remedy, it's essential to recognise a brain tumour in its earliest stages. More than a million people are diagnosed with brain tumours each year worldwide, according to the International Agency for Research on Cancer (IARC), and the death rate is increasing. The occurrence of abnormal tissues is frequently easier to detectable during brain tumour studies, it still these abnormalities cannot be accurately segmented or characterised. In the current scenario, radiologists must manually examine tumours using medical imaging technologies and then produce a report. Despite significant progress, segmenting brain tumours from MR images in a timely, accurate, authentic, and reproducible manner still a challenge. To address this issue, this analysis proposes a system that detects tumours and classifies them as benign or malignant using image processing is combined with machine learning. So, in conventional methods for early precise identification of tumour cells, there are numerous algorithms that help to diagnose the tumour cells but fail to forecast an exact outcome. For performance analysis, accuracy, sensitivity, and recall are used as parameters.



**KEYWORDS:** **Brain Tumor, MR Images, Computer Aided Detection System(CAD), Convolutional Neural Network (CNN).**
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## I. INTRODUCTION

With billions of cells working together, the brain is one of the human body's most complicated organs. This cerebral tumour is an abnormal collection of cells that develops as cells are divide uncontrolled and around or occurs inside the brain. This cell group is capable of killing healthy cells and interfering with brain activity. There are two types of brain tumours: low-grade described as benign and high-grade described as malignant. The presented method aims to differentiate between benign or malignant brain tumours and the normal brain. Glioblastoma, sarcoma, and metastatic bronchogenic carcinoma tumours are a few examples of the types of brain tumours that may be studied using brain Magnetic resonance imaging (MRI). In order to identify and classified MRI brain tumours, several wavelet techniques and support vector machines are used. It takes a lot of time and effort for doctors to manually find a brain tumour. Identification and classification of brain tumours might be performed automatically to prevent misclassification and save time.

There are many people affected by brain tumours all over the world; it can may be found at early ages; this is not just limited to old age group. Cells in the brain's cranium developed in an unusual growth, resulting in the growth of a tumours. The brain's abnormal cell development has an impact on regular brain activity, which leads to irregular human body functioning and improper health behaviours.

The ability to detect brain tumours in early stages has been made possible by developments in Machine learning (ML) and Image processing (IP). In order to diagnose tumours, it is essential for imaging these tumours more precisely. High resolution methods including Positron emission tomography (PET), CT scans, Magnetic resonance imaging (MRI) and other types are included. An important mean for studying the visceral structures of the body is MRI. In these cases, MRI is commonly presented because it generates images of the brain and cancerous tissues that are of greater quality than those obtained by other medical imaging procedures.

With regard to several applications of brain tumours, the rapid development of machine learning algorithms has been extremely important in the prediction of brain cancer. Clinicians can make quicker decisions because to the capabilities of medical imaging technologies to create images of inside organs, tissues in the body, more accurate diagnoses inform treatment plans. More specifically, medical imaging methods are used to diagnose brain tumours [8]. As a complementary approach to enhance the performance of radiological diagnosis and detection, computer-aided diagnosis and detection systems utilising the image characteristics retrieved from brain tumours have been reported [9].

As the world's population grows, cancer is becoming an increasingly important health issue. Statistics show that 7.6 million people die from cancer each year in India, while there are an estimated 12.7 million cancer patients [18]. When normal cells are old or damaged, they typically die and are replaced by new cells. This approach can sometimes be wrong. Old or damaged cells do not die when the body does not require new cells to be created. A tumour, also known as a growth, is a mass of tissue generated by the accumulation of additional cells. Primary brain tumours are described in two different types: malignant and benign. There are no cancer cells in benign brain tumours. Usually treatable, benign tumours rarely return after removal. Most benign brain tumours have a distinct border or edge. Rarely do benign tumour cells spread into nearby tissues. They don't spread to other parts of the body and are not infectious. In malignant brain tumours, also referred to as brain cancer, there are cancerous cells present. Brain tumours that are malignant are more dangerous and can be life-threatening threat. Cancer cells can break free from malignant brain tumours and affect the spinal cord or other brain tissue. In very exceptional cases, they may spread to a few other parts of the body.



The abnormal development of brain tissue that causes brain tumours fill up the required amount of brain space. There are many various types of brain tumours, and 120 different types have still been approved by medical science [1]. Every form of tumour is not malignant, and people with cancerous brain tumours frequently survive for five years on average. Cancerous tumours spread more quickly and represent a serious threat to the survival of patients. Meningioma, pituitary, and glioma are three types of tumours that have gained a mainstream. Pituitary and meningioma tumours are not usually cancerous, yet glioma tumours develop quickly and are dangerous [2]. For patients with brain tumours of the glioma type, the average survival time is 12–18 months. To save the patient's life, early diagnosis and treatment are essential. Without human supervision, identifying medical images is not a simple process. This is a revolutionary development made possible by artificial intelligence (AI), and different AI algorithms provide the ability to make decisions similarly to humans. The remainder of the analysis is structured in the following order: The Literature Survey is explained in Section II, Section III explains Design a computer-aided Diagnosis System For Brain Tumour Classification Using CNN. The experimental results analysis is presented in Section IV, and Section V concluded with the analysis.

## II. LITERATURE SURVEY

Hemanth, G. et al.,[ 3] describes the machine-learning-based classification that was done using "LinkNet," a low-density transfer learning system. Before feature extraction, images were preprocessed by being filtered, segmented, and etc. In addition to CNN, the authors also used random fields, SVM, and genetic algorithms. In comparison to other models, the presented CNN model has the best accuracy.

Raducu Gavrilescu,Cristian Zet, Marcin Skoczylas, Cristian Fosalau, David Cotovanu et al., [4] The majority of current detection and diagnostic methods depend on the decision of neurospecialists and radiologist for image analysis: which is time-consuming and prone to human error. Brain tumours are one of the most serious illnesses require early and accurate detection methods. This study reviews describes the methods and procedures used in the detection of brain tumours using Magnetic resonance imaging (MRI) and Artificial neural networks (ANN) techniques. After collecting the image data, CAD executes the various stages as follows: the first stage is pre- processing and post-processing of MRI images to enhance it and make it more suitable to analysis; then applied threshold to segment the MRI images. In the second stage, features were extracted from images using statistical feature analysis, which generated the features based on the Spatial grey level dependence matrix (SGLD) of the images. Then choose the most appropriate and effective attributes to locate the tumour. The third stage involved the building of artificial neural networks; the feedforward back propagation neural network with supervised learning was used as an automated to categorize the images under investigation as either having tumours or not. The network's performance was successfully tested, analyzed, and optimized.

Nitu Kumari,Sanjay Saxena et al., [ 5] explains a Brain Tumour Segmentation and Classification. Brain cancer affects thousands of people annually. Segmenting, detecting, and extracting the contaminated tumour region from magnetic resonance imaging is the greatest significance, but it takes time and there is a chance of human errors, as we can see from the diagnostic rating. To address these constraints, semiautomatic and automated approaches for segmentation and classification are now used. For segmentation, they recommend using k-means clustering and Otsu thresholding. Grey level occurrence matrix and support vector machine are used to further classify images after extracting textural-based information.



Parnian A., Arash M., Konstantinos N. et al.,[6] utilized CapsNet, a pre-trained network, to enhance feature extraction and considering on the classification problem for brain tumours. One convolution layer and 64 feature maps were used by the authors to implement a new CapsNet architecture and obtain accuracy. Tang Zhenyu, Yap Pew-Thian, Ahmad Sahar, Shen Dinggang et.al, [7] MAS(Multi-Atlas Segmentation) is presented as a new framework for MR tumour brain images. In basic terms, MAS creates a new brain image for segmentation by recording and fusing label data from many normal brain atlases. Tumour brain images remain a challenging problem, despite the fact that they are usually configured for normal brain images. At the first level of the MAS framework, a new low-rank algorithm is being used to retrieve the recovered images of the normal brain from the MR tumour brain image by using the information from the normal brain atlas. The images will be recovered without being impacted by tumours in the following stage, which involves registering normal brain atlases. Garima Singh, Dr. M.A. Ansari et.al, [10] the Median filter, Un-sharp masking filter, Averaging filter, and Gaussian filter are some of the image de-noising filters used to eliminate additive noises present in MRI images. Other filters include salt and pepper noise, Gaussian noise, and speckle noise. The de-noising performance of all the solutions considered is compared using Peak signal-to-noise ratio (PSNR) and Mean square error (MSE). The use of normalized histogram and segmentation through the K-means clustering algorithm is a novel approach that is recommended for effective brain tumour diagnosis. G. Rajesh Chandra, Dr. Kolasani Ramchand H Rao, [11] explains that diagnose brain tumours using MRI images. The MRI scan often generates a large amount of data, making the manual categorization of tumour versus non-tumor extremely time consuming. While only supporting a small amount of images, it provides exact quantitative measurements. To lower the human death rates, automated categorization methods that can be trusted are thus required. Given the significant structural and spatial inconsistency of surrounding brain tumour locations, automated brain tumour categorization is frequently quite challenging. The CNN classification was used to propose an automated brain tumour detection approaach.

## III. DESIGN A COMPUTER-AIDED DIAGNOSIS SYSTEM FOR BRAIN TUMOR CLASSIFICATION USING CNN

In this analysis, Design a Computer-aided Diagnosis System For Brain Tumor Classification Using CNN is presented. The Fig. 1 shows the architecture of presented model.

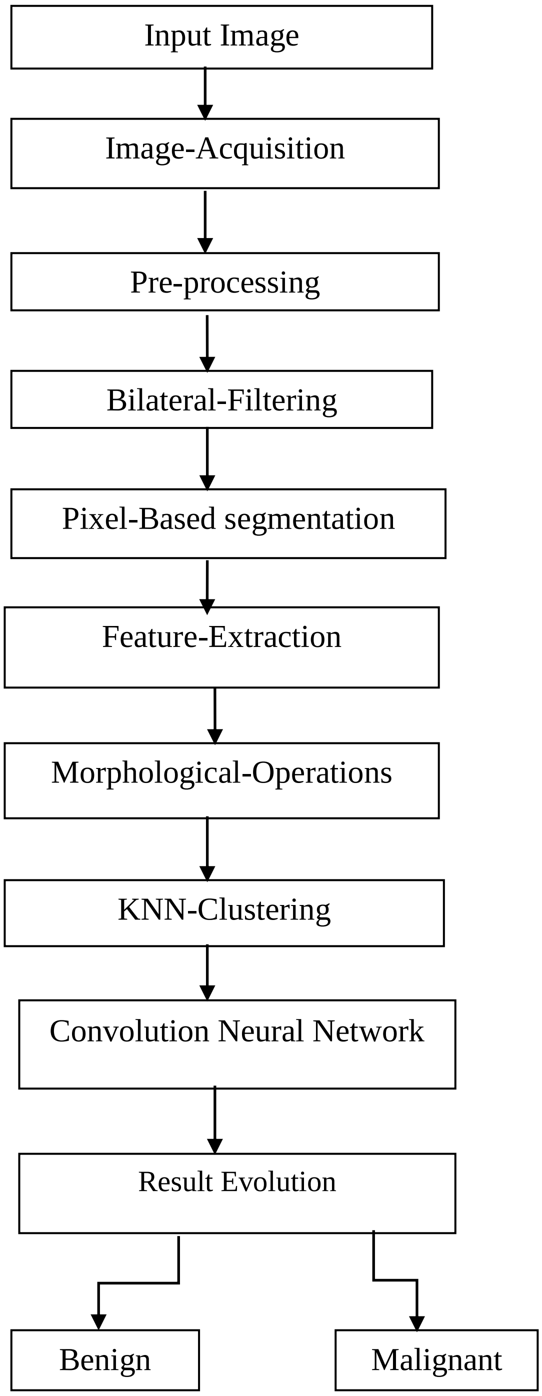




**Fig. 1: The architecture of presented model.**

The classifier classifies the images in accordance with the characteristics of the input data. There are advantages and disadvantages to every classifier. In order to make the identification of brain tumours considerably simpler, this work describes that to create a software tool. This method is based on images from MRI scans. In order to accurately predict outcomes and make decisions for patients survival by identifying tumours at an early stage, this analysis presents a well-defined platform for medical clinics and doctors. The tool includes stages for noise removal, feature extraction, and classification of the picture into two areas, apecifically, an area impacted by a tumour or not. Noise reduction consists of the elimination of all unwanted regions or parts from the image during the procedure. This can sometimes result in the removal of essential sections of the image. To avoid this, they need to use an effective noise reduction technique.

The acquisition of an RGB(red, green, blue) image is the initial stage. The original MRI brain image has a resolution of 256*256*3 pixels, which is reduced to 256*256 pixels after conversion to grayscale. After capturing the image, it is converted to grayscale and the contrast is enhanced to a specified level. The contrast image is divided into two types: left and right. Threshold / Binarization transforms images with up to 256 grey levels to black and white. This image segmentation refers to the process of dividing a image into several regions or parts.. The main objective is to make the representation in images are simpler or different so that it can be analyzed more quickly and with more effective. Objects and boundaries in images are located using this technique. Every pixel in a image is labelled, such that pixels with the same label have certain characteristics.

The first step in image processing is pre-processing. To ensure that all subsequent image processing is done on same -sized images, the image is resized in the proposed work. The image is changed to grayscale in the next step. Now, grayscale versions of the RGB images are created. A data matrix whose values correspond to different shades of grey creates a grayscale image. Data integration, data cleaning, data resizing, data reduction, data transformation, etc. are all part of the image pre-processing approach. During the pre-processing of an image, unnecessary information is removed, noisy data is smoothed up, outliers are found and eliminated, data inconsistencies are corrected. Finally, normalization and aggregation are carried out. Image-processing techniques are frequently to be quite useful in determining specific heart images, eliminating noise, and improving picture quality.

Filtering, often known as salt-and-pepper noise reduction is a nonlinear approach for reducing impulsive noise. It is also helpful in retaining image edges while decreasing random noise. The bilateral filtering generates a result of 10, which is the median of the five values, at the present pixel spot. When determining whether a pixel in an image is representative of its surrounds, the median filter looks at each pixel in the image separately and compares it to its neighbours.

Segmentation in medical imaging is a difficult and time-consuming procedure for accurately identifying brain tumours. A number of clinical trials are being conducted to identify the pattern of a brain tumour. Partitioning the image into many segments makes it more understandable and simple to analyze. This is the basic goal of segmentation. Each pixel in the image is assigned a label, such that pixels with the same label exhibit comparable features and attributes. The mapping and identification of tumour clustering technique has proven extremely successful for the anatomical detailed information of brain images. Image segmentation methods include edge detection methods, region growth methods, watershed segmentation, and clustering segmentation.



Following segmentation, features from the images must be extracted for further processing; this is done in three steps: first, Discrete wavelet transform (DWT), second, Principal component analysis (PCA), and finally, structural, statistical, and texture features are obtained from the PCA output. Morphological procedures come next after pre-processing. Dilation and erosion are the two most basic morphological activities. Dilation is a process that "grows" or "thickens" particular sections of an image, the specificity and degree of is controlled by a shape known as the structural element. In contrast, erosion "shrinks" or "thins" certain regions of a binary image. The same structural element that controls dilation also controls the method and degree of shrinkage. The modified image is then grouped using the same 'disk' organizing element that was used to create. The clustering process comprises dilation and erosion, followed by a 'open' procedure. Following all of these actions, the image's related components are returned.

Convolutional Neural Network - Convolutional Neural Network is a subset of Deep Neural Network that is widely used in image categorization. CNN's main component is the neuron, which has learnable characteristics such as biases and weights. Convolution layer, pooling layer, and normalization layer are the three main layers that made up the CNN structure. Filters are used by the convolutional neural network to extract image information. The feature maps are created using filters, and the features are extracted. Neurons are activated by the activation function. CNN is a tool for image segmentation. It extracts features directly from pixel images with minimal pre-processing required. In applications for image identification, CNN is an important deep learning methodology. Convolution and pooling are the two fundamental techniques used. Up until a high degree of classification accuracy has been achieved, convolution and pooling layers are constructed. Every convolution layer also contains a small number of feature maps, and weights associated with convolution nodes (in the same map) are shared.

In the standard CNN objective function, the presented method uses a mean field term. The image processing tool is used to create and apply the approach. The University of california irvine (UCI) datasets are used to assembled the datasets. All of the attributes are compared, and the overall result is presented in the figures. The accuracy is calculated and compared to the rest of the state-of-the-art procedures. The suggested brain tumour classification approach's efficiency and training accuracy is estimated.

The majority of cancers are life-threatening, with brain tumours being one among them. Brain tumours are often divided into two types. Tumours are both benign and malignant. Benign tumour cells develop slowly and stagnantly do not spread to other regions of the body. Malignant tumour cells are cancerous cells made up of out-of-control cells that can impact other adjacent tissues and have the ability to migrate to other sections of the body. The term "primary brain tumour" refers to cancers that originate in the brain; "secondary brain tumour" refers to tumours that develop in the brain as a result of cancers in other organs.



## IV. RESULT ANALYSIS

In this section, the result analysis of presented Design a computer-Aided Diagnosis System For Brain Tumour Classification Using CNN. A small number of parameters are calculated and analyzed for evaluation of performance and assessing system stability. These are as follows: Recall, sensitivity, and accuracy of the training and testing sets, together with overall performance, were used to evaluated the presented CNNs performed. All of the features are compared, and the overall result is presented in the figures. The accuracy is calculated and compared to the rest of the state-of-the-art procedures. The suggested brain tumour classification approach's efficiency and training accuracy are calculated. TN (True Negative) represents the prediction for people are did not have a brain tumour but were diagnosed tumor, FN (False Negative) represents indicates a diagnosis for people are did not have a brain tumour but had that was discovered, TP (True Positive) indicates the prognosis for people are have brain tumours and have been diagnosed tumor, and FP (False Positive) indicates the likelihood of a brain tumour in individuals are were first found to be tumor.

Accuracy: The classifier's accuracy determines the rate of accurate predictions.

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \quad (1)$$

Sensitivity: The ratio of accurately classified positives to really positives is known as a classifier's sensitivity.

$$Sensitivity = \frac{TP}{FN+TP} \times 100 \quad (2)$$

Recall: Recall types represent several classifications of accurate tumours.

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

The main goal of this analysis is to create an intelligent expert system that can classify brain tumours using deep CNN and SVM.

**Table 1: PERFORMANCE METRICS EVALUATION**

| Performance Metrics | SVM Based Diagnosis System | Presented CNN approach |
|---|---|---|
| Accuracy | 75.7 | 88.7 |
| Sensitivity | 79.7 | 90.5 |
| Recall | 85.6 | 93.7 |



The accuracy comparison between the presented CNN technique and the SVM-based approach is shown in Fig. 2.

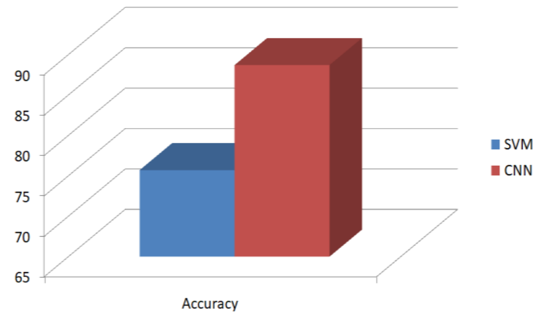


**Fig. 2: Accuracy comparison between svm based and presented cnn approaches**

The sensitivity comparison between the presented CNN technique and the SVM-based strategy is shown in Fig. 3.

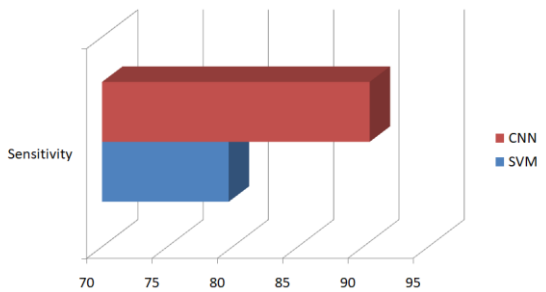


**Fig. 3: Sensitivity comparison between svm based and presented cnn approaches**

The recall comparison between the given CNN technique and the SVM-based strategy is shown in Fig. 4.

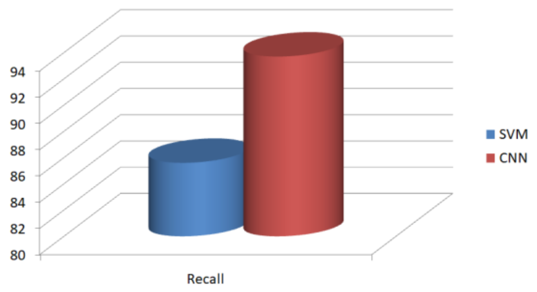


**Fig.4: Recall comparision between svm based and presented cnn approaches**

## V. CONCLUSION

In this analysis, Design a computer-Aided Diagnosis System For Brain Tumour Classification Using CNN is presented. The primary aim of the presented analyssis is to create a brain tumour classification model that is accurate for non-identical datasets and useful for classifying brain tumours. The presented strategy accurately segmented tumours and identified them as benign or malignant. The analysis is performed on these two datasets, as well as the combination of these two databases. Future research should concentrate on better classifying tumour stages so that the exact location of the tumour may be estimated. This may be essential to prompting additional treatment after a tumour diagnosis and can aid in early tumour detection. This will save the life of a person. After preprocessing and augmentation, custom CNN-based deep feature extraction is performed. The MR images are evaluated. The proposed model performs well in terms of effective test prediction. In terms of accuracy, sensitivity, and recall, the provided CNN design outperforms the other based architectures.

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