# Study And Compare Machine Learning Techniques Using Medical Image

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***Abstract***- *Brain tumours are dangerous and serious disorders affected by uncontrolled cell growth in the brain. Brain tumours are one of the most challenging diseases to cure among the different ailments encountered in medical study. Early classification of brain tumours from magnetic resonance imaging (MRI) plays an important role in the diagnosis of such diseases. There are many diagnostic imaging methods used to identify tumours in the brain. MRI is commonly used for such tasks because of its unmatched image quality. The traditional method of identifying tumours relies on physicians, which is time-consuming and prone to errors, putting the patient's life in jeopardy. Identifying the classes of brain tumours is difficult due to the high anatomical and spatial diversity of the brain tumour's surrounding region. An automated and precise diagnosis approach is required to treat this severe disease effectively. The relevance of artificial intelligence (AI) in the form of deep learning (DL) has revolutionized new methods of automated medical image diagnosis. As a result, good planning can protect a person's life that has a brain tumour. Using the 2D Convolutional Neural Network (CNN) technique, this project proposes Computer-Aided Diagnosis (CAD) a deep learning-based intelligent brain tumour detection framework for brain tumour type (glioma, meningioma, and pituitary) and stages (benign or malignant). CNN is used to classify tumours into pituitary, glioma, and meningioma. Then its classify the three grades of classified disease type, i.e., Grade-two, Gcrade-three, and Grade-four. In this project, we provide a performance comparison of four popular algorithms for brain tumor detection: K-Nearest Neighbors (KNN), Support Vector Machines (S VM), Fuzzy Logic (FL), and Convolutional Neural Networks (CNN). The performance of the models is evaluated using performance metrics such as accuracy, sensitivity, precision, s pecificity and F1-score. From the experimental results, our proposed CNN model based on the Xception architecture using ADAM optimizer is better than the other three proposed models. The Xception model achieved accuracy, sensitivity, precision specificity, and F1-score values of 99.67%,99.68%, 99.68%, 99.66%, and 99.68% on the MRI-largedataset. The proposed method is superior to the existing literature, indicating that it can be used to quickly and accurately classify brain tumours.*

***Keywords***- K-Nearest Neighbors (KNN), Support Vector Machines (S VM), Fuzzy Logic (FL), and Convolutional Neural Networks (CNN).

## I. INTRODUCTION

Deep Learning is a part of machine learning, which is a subset of Artificial Intelligence. It enables us to extract the information from the layers present in its architecture.

It is used in Image Recognition, Fraud Detection, News Analysis, Stock Analysis, Self-driving cars, Healthcare like cancer image analysis, etc.

### Types of Brain Tumour

There are many types of brain tumours. Each type can differ in growth rate, typical location, size at the time of diagnosis, and who they affect. Brain tumours are the most common type of tumour in children, and the second or third most common type in young adults (breast cancer is highest in females). Some brain tumour types affect males more often than females, or vice versa. The following are a few of the more common brain tumours and the percentage of the tumour count among all brain and other central nervous system (CNS) tumours.

**Fig: Different types of brain tumors. Meningioma (left), glioma (center), and pituitary tumor (right) are among the most common brain tumor types.**

**Meningioma (38%)** arises from the membranous covering of the brain (meninges). Most are benign and grow slowly inward from the meninges to push on the brain and surrounding structures.

**Glioma (25%)** arises from glial cells that surround and support the neurons of the CNS. Tumours in this category are further classified according to the type of glial cell from which they originate (astrocytoma, glioblastoma multiforme, ependymoma, oligodendroglioma, mixed glioma). Although some types are relatively benign, gliomas comprise 80% of malignant brain or other CNS tumours.

**Pituitary tumour (17%)** arises from the pituitary gland at the base of the brain. The pituitary gland is important for normal hormone release. Most pituitary tumours are benign. However, large tumours can compress nearby nerves and tissues, causing vision defects and hormone abnormalities.

Other brain tumour types include acoustic neuroma, craniopharyngioma, chordoma, chondrosarcoma, or brain metastases. Most brain metastases arise from cancers in the lung, breast, colon and rectum, skin (melanoma), and kidneys (renal cell carcinoma). In adults, brain metastases are more common than primary brain tumours.

Brain tumours can arise from tissues within the brain (primary brain tumour) or from a cancer located elsewhere in the body (secondary or metastatic brain tumour). Benign brain tumours typically grow slowly and stay within the brain without invading surrounding tissues. In contrast, malignant brain tumours can grow quickly and spread to other body parts through a process called metastasis.

## II. RELATED WORKS

Brain tumours are dangerous and serious disorders affected by uncontrolled cell growth in the brain. Brain tumours are one of the most challenging diseases to cure among the different ailments encountered in medical study.

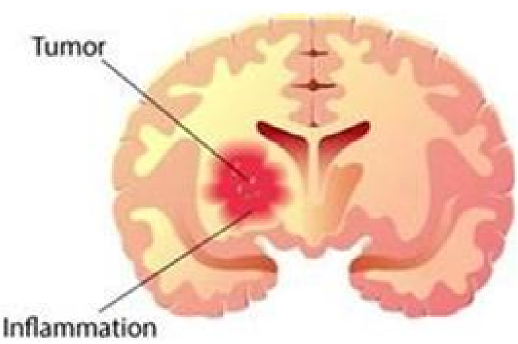



**Fig: Brain Tumour**

Early classification of brain tumours from magnetic resonance imaging (MRI) plays an important role in the diagnosis of such diseases. As a result, good planning can protect a person's life that has a brain tumour. Using the 2D Convolutional Neural Network (CNN) technique, this project proposes Computer- Aided Diagnosis (CAD) a deep learning-based intelligent brain tumour detection framework for brain tumour type (glioma, meningioma, and pituitary) and stages (benign or malignant). CNN is used to classify tumours into pituitary, glioma, and meningioma. Then its classify the three grades of classified disease type, i.e., Grade-two, Gcrade-three, and Grade-four.

In this project, we provide a performance comparison of four popular algorithms for brain tumor detection: K-Nearest Neighbors (KNN), Support Vector Machines (SVM), Fuzzy Logic (FL), and Convolutional Neural Networks (CNN).

**CNN (Convolutional Neural Networks)**

A CNN is a type of deep learning used to analyse visual scenes. It is characterized by having one or more hidden layers, which extract the attributes in videos or images, and a fully connected layer to produce the desired output. Whereas for the computer, the image is a 3D array (width × height × depth) of values ranging from 0 to 255. It is simply pixels of colour; if the number of channels is one, the image is grayscale, black, and white. Besides, the channels are three colours (if images are RGB). CNN Deep Network has shown outstanding performance in many competitions related to image processing due to its accurate results. CNN is a hierarchical structure that contains several layers.

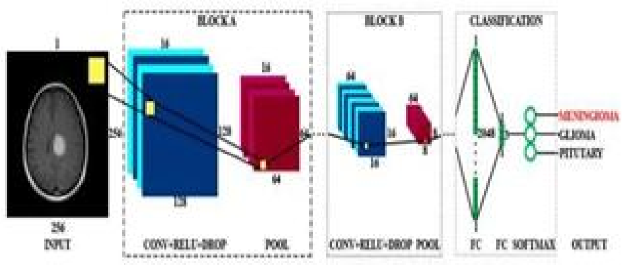



**Fig.Architecture of Convolutional NeuralNetworks**

## III. PROBLEM DESCRIPTIONS

In this project, we present a new CNN architecture for brain tumor classification of three tumor types: meningioma, glioma, pituitary tumor and their grades from T1-weighted contrast- enhanced magnetic resonance images.The proposed framework model includes four stages. First, the input MR image is pre- processed (noise filter, resize and binarization). Firstly, we prepared the dataset by creating the annotations for input images to specify the exact location of tumors. Next, we trained the model using created annotations for tumor localization and classification.During training, an input sample along with the bounding box annotation is passed to the improved CNN framework.A typical CNN can easily be divided into two main parts: extraction of features and classification/prediction. The general architecture of the CNN models has five main layers (input, convolutional, pooling, fully connected, and classification). The convolutional and pooling layers are used to extract the features, whereas the fully connected layers and classification layers are used for prediction/classification. Finally, the pre-trained 2-class model was re-utilized using the transfer-learning method in order to re-adjust the weights of neurons to categorize the tumors into subclasses (glioma tumor, meningioma tumor, and pituitary tumor) and their grades.

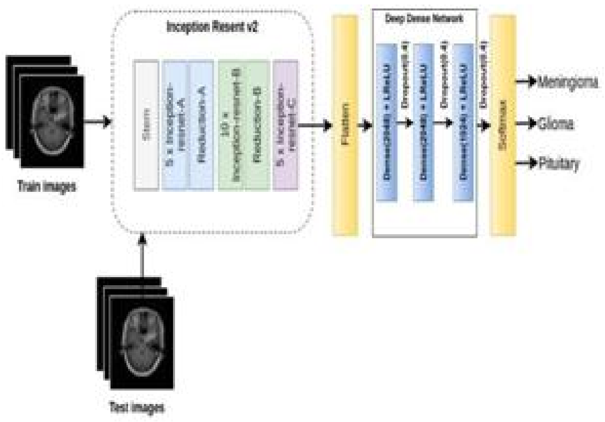



**Fig: Problem Description**

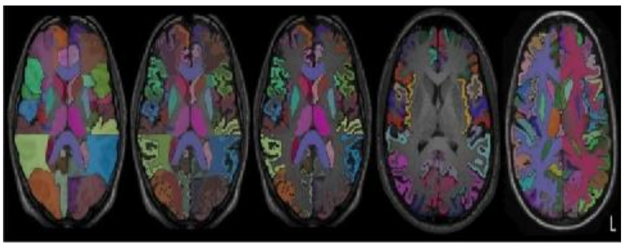


**Fig: Classification Of Brain Images**

**FEATURE EXTRACTION**

Medical images contain tumours characterized by different locations and different types of pathologies, shape, size, density, as well as the size of the area of the affected tissue near the tumour space. For generating images and classifying the pixels in each image, we need to extract the features of original images. In the proposed networks, the construction of the feature extraction part which combines a bottom-up pathway and a top- down pathway. The key of generating images and segmenting images depends on the feature representation. There exit two tasks in this approach: generating segmentation images and discriminating the class of each pixel in each image.

**DCNN**

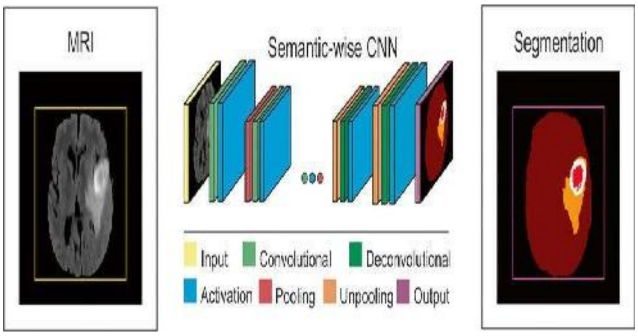



**Fig: DCNN Workflow**

The DCNN model is designed to work in all circumstances with the advanced features of deep learning techniques which paved the system to focus on not to affect with overfitting. CNN model is used to fix the input volume size as 64*64*3 and the receptive field volume size is 3*3, because each neuron is connected with all preceding layer neurons, so practically it is impossible to deal with such high dimensional inputs. Volume size of every neuron is 5*5*3(width, height, and depth), totally 75 weights and 1 bias parameter. Parameter sharing is considered in CNN for reducing the number of parameters in complete process. The research is carried out to meet the challenges identified in under water communication and the image classification is unsolved with various issues to be addressed. It is an open problem for the research community to come up with an effective approach to meet the requirements. DUOCM is proposed for analysing the effectiveness of underwater image classification.

A CNN method is used to predict the bounding boxes and classification probabilities. For the Tumor detection, the targets are difficult to be identified from the background. In order to improve the detection accuracy, the whole image information is used to predict the bounding boxes of the targets and classify the objects at the same time; through this proposal, the end-to-end real time targets detection can be realized.

The corresponding ground truth segmentation images encompass the followingintra-tumoral structures (and the background) as classes:

0. Normal(No),1. Meningioma, 2. Glioma, 3. Pituitary

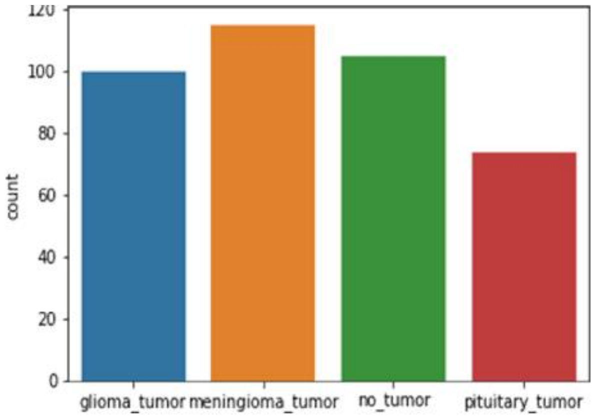



**Fig: No. of Disease Count In Brain Tumour Types**

## IV. TESTING PHASE

**Prediction**

After completing the training process, the algorithms have been evaluated from the test dataset containing tumor in various conditions.

Prediction Network

The goal of this detection network is to generate final bounding box by consideringinputs from Feature Network and Regional Proposal Network. It consists of 4fully connected layers which are in turn interconnected to bounding box regressionlayer and classification layer that help to generate final detections.

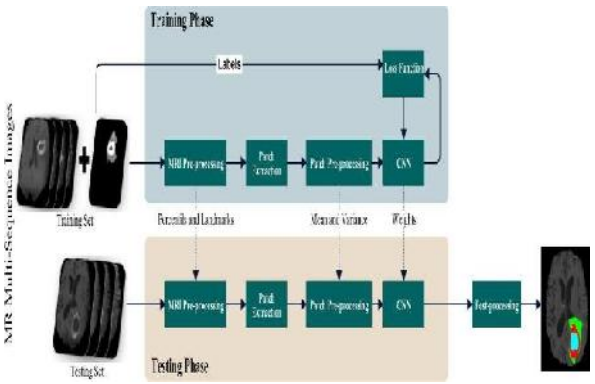



**Fig: Testing Phase of Workflow**

**Performance Metrics**

There are several ways to evaluate the performance of a classifier, but we used a confusion matrix-based metric to validate the results. The performance metrics such as accuracy, precision, sensitivity, specificity, F1-score, to assess these indicators, we needed to calculate thefollowing values - true positive, false negative, true negative and false positive.

True Positive (TP) is the number of positive predicted cases and they are actually positive.
True Negative (TN) is the number of negative predicted cases and they are also actually negative.
False Negative (FN) is the number of negative predicted cases while they are actually positive, also called (type two) error.
False Positive (FP) is the number of positive predicted cases while they are actually negative, also called (type one)error.

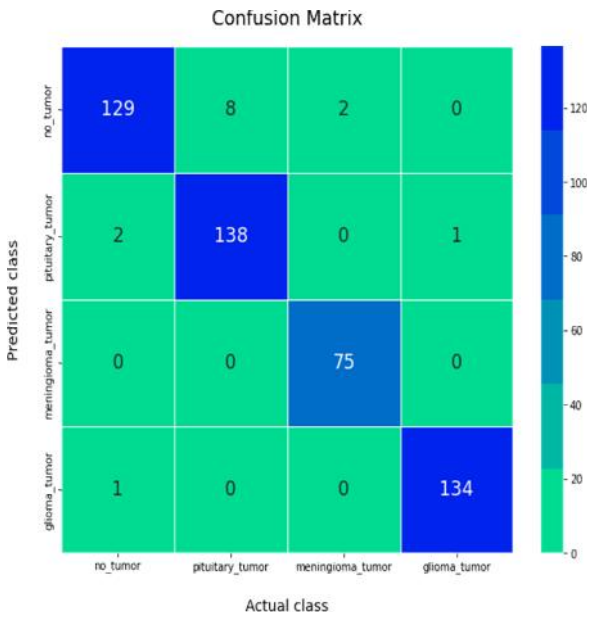



**Fig: Confusion Matrix**

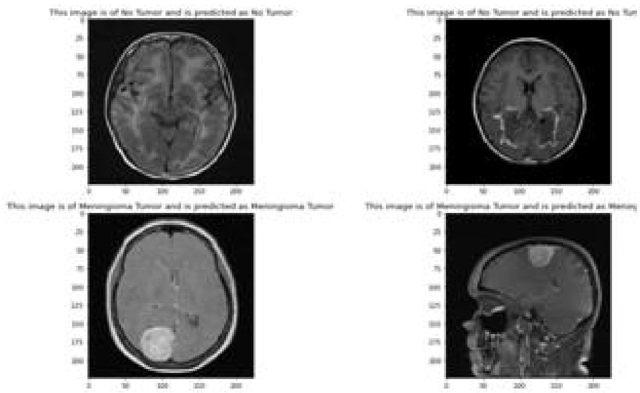


**Fig: Predicted Measures**

Convolutional Neural Networks (CNN) is a deep learning algorithm that has shown great success in image classification tasks. CNN is particularly effective in identifying patterns and features within medical images, such as MRIs, CT scans, and X- rays. In the context of brain tumour disease prediction, CNN can analyse medical images of the brain and detect the presence of tumours. Support Vector Machine (SVM), K-Nearest Neighbour (KNN), and Fuzzy Logic algorithms are traditional machine learning algorithms that are commonly used for classification tasks.

These algorithms are also used in the medical field for disease prediction tasks. SVMs work by finding the best hyperplane that separates the data points into different classes, while KNN works by finding the k-nearest neighbours to a given data point and classifying the data based on the most common class among the neighbours. FL is a rule- based algorithm that uses fuzzy sets to represent uncertainty and imprecision in the data. The main difference between using CNN and these traditional machine learning algorithms for brain tumour disease prediction lies in the type of data being used. CNN is particularly suited for analysing medical images and identifying patterns and structures within the images, while traditional machine learning algorithms are better suited for analysing numerical data and features extracted from the images. In terms of performance, CNN has shown to outperform traditional machine learning algorithms in image classification tasks, including medical image analysis. However, CNN may require more computational resources and training data than traditional machine learning algorithms.In summary, the choice of algorithm for brain tumour disease prediction depends on the type of data being used and the performance requirements of the task. CNN is a powerful algorithm for image-based disease prediction, while traditional machine learning algorithms may be better suited for numerical data and feature-based disease prediction.

| No | Model | Accuracy | Precision | Recall | F1 Score |
|---|---|---|---|---|---|
| 1 | KNN | 0.73631 | 0.73331 | 0.73631 | 0.74834 |
| 2 | SVM | 0.8201 | 0.82911 | 0.8201 | 0.82319 |
| 3 | FL | 0.83148 | 0.87527 | 0.84742 | 0.85236 |
| **4** | **CNN** | **0.95859** | **0.97684** | **0.96865** | **0.98457** |

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

$$Precision = \frac{TP}{TP+FP}$$

$$Recall = \frac{TP}{TP+FN}$$

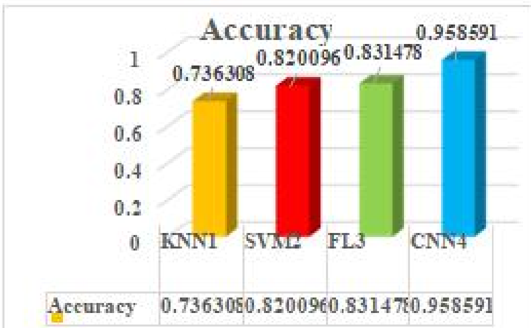
$$F1\ Score = 2 * \frac{Precision * Recall}{Precision + Recall}$$

The performance comparison of different machine learning algorithms for the detection of brain tumors can depend on various factors such as the size of the dataset, the quality of the features, and the specific implementation of the algorithms. However, here is a general overview of the performance of K- Nearest Neighbors (KNN), Support Vector Machines (SVM), Fuzzy Logic (FL), and Convolutional Neural Networks (CNN) for brain tumor detection.

KNN is a simple algorithm that classifies an input sample based on its k nearest neighbors in the training dataset. It can be effective for small datasets but may not perform well for large or complex datasets. For brain tumor detection, KNN can achieve high accuracy if the feature extraction process is well- designed, and the dataset is not too large. However, it may not be suitable for large-scale applications due to its computational complexity.

SVM is another popular algorithm for classification tasks, including brain tumor detection. SVM aims to find a hyperplane that separates different classes in the feature space. SVM can achieve high accuracy when the features are well-defined and the dataset is well-balanced. SVM is computationally efficient and can handle large datasets well. However, SVM may not perform well when there is a high degree of overlap between classes or when the dataset is imbalanced.

FL is a rule-based algorithm that uses fuzzy sets to represent uncertainty and imprecision in the data. FL can be effective for brain tumor detection when the dataset is noisy or when the features are not well-defined. FL can handle uncertainty and imprecision in the data, making it a suitable choice for certain types of datasets. However, FL may not perform well when the dataset is well-defined or when the features are highly correlated.




CNN is a deep learning algorithm that uses convolutional layers to extract features from images. CNN can achieve state-of-the- art performance for brain tumor detection, especially when the dataset is large and the images are high-resolution. CNN can handle complex datasets with many features and can learn hierarchical representations of the data. However, CNN requires a large amount of training data and can be computationally expensive.In summary, the choice of algorithm for brain tumor detection depends on the specific requirements of the task, including the size and quality of the dataset, the features used, and the computational resources available. KNN, SVM, FL, and CNN can all be effective for brain tumor detection, depending on the specific implementation and application.

## V. CONCLUSION

The latest developments in medical imaging tools have facilitated health workers. Medical informatics research has the best options make good use of these exponentially growing volumes of data. Early detection options are essential for effective treatment of brain tumors.This project presented a CAD approach for detecting and categorizing BT's radiological images into three kinds (pituitary-tumor, glioma-tumor, and meningioma-tumor). We also classified glioma-tumor into various categories (Grade-two, Grade-three, and Grade-four) utilizing the DCNN approach (i.e., our proposed work). Firstly, pre-trained DensNet201 deep learning model was used, and the features were extracted from various DensNet blocks. Then, these features were concatenated and passed to softmax classifier to classify the brain tumor. Secondly, the features from different Inception modules were extracted from pre-trained Inceptionv3 model and concatenated and then, passed to the softmax for the classification of brain tumors.The proposed method produced 98.51% testing accuracy on testing samples and achieved the highest performance in detection of brain tumor.The outcome of the presented architecture shows high training and validation accuracy with low training and validation loss. Moreover, the testing phase determines the overall portable EM imaging system's capability and potential of CNN architecture in detecting and localizing the brain tumor with high accuracy.

## VI. FUTURE SCOPE

In the future, we are going to increase MRI images in the used dataset to improve the accuracy of the proposed model. Moreover, Applying the proposed approach to other types of medical images such as x-ray, computed tomography (CT), and ultrasound may constitute a principle of future studies.

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