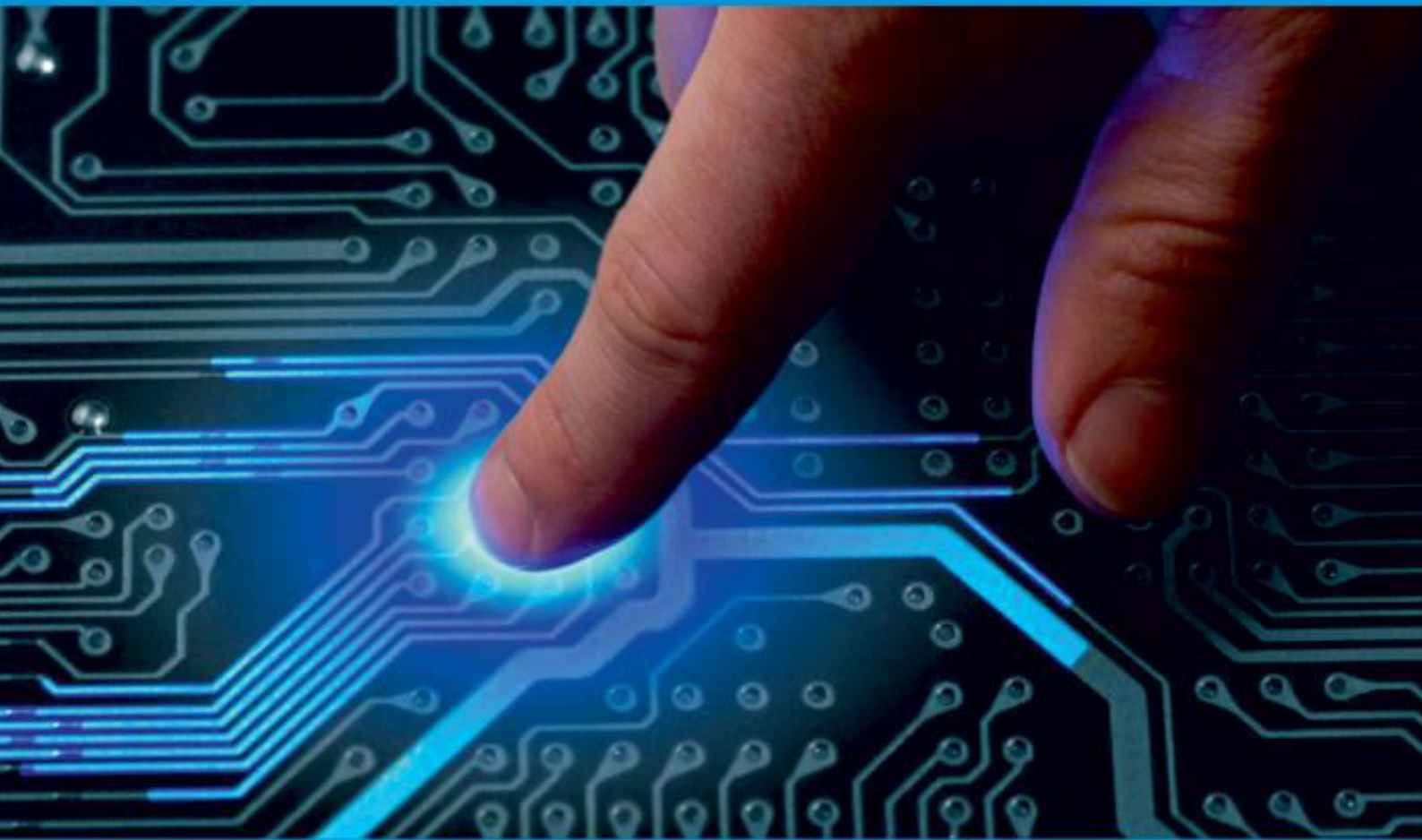




IJIRCCCE

e-ISSN: 2320-9801 | p-ISSN: 2320-9798



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH


IN COMPUTER & COMMUNICATION ENGINEERING

Volume 9, Issue 11, November 2021

ISSN INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA

Impact Factor: 7.542

 9940 572 462

 6381 907 438

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 www.ijircce.com

Implementation of High-order Feature Learning for Multi-atlas based Label Fusion: Application to Brain Segmentation with MRI

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ABSTRACT: The brain tumors, are the most common and aggressive disease, leading to a very short life expectancy in their highest grade. Thus, treatment planning is a key stage to improve the quality of life of patients. Generally, various image techniques such as Computed Tomography (CT), Magnetic Resonance Imaging (MRI) and ultrasound image are used to evaluate the tumor in a brain, lung, liver, breast, prostate...etc. Especially, in this work MRI images are used to diagnose tumor in the brain. However the huge amount of data generated by MRI scan thwarts manual classification of tumor vs non-tumor in a particular time. But it having some limitation (i.e.) accurate quantitative measurements is provided for limited number of images. Hence trusted and automatic classification scheme are essential to prevent the death rate of human. In this paper we used CNN to classify (tumor or no tumor) and to find out percentage of tumor. Proposed system can also be used to surf similar kind of tumor related images from internet.

KEYWORDS: MRI image, CNN, Brain Segmentation

I. INTRODUCTION

Brain tumor is one of the vital organs in the human body, which consists of billions of cells. The abnormal group of cell is formed from the uncontrolled division of cells, which is also called as tumor. Brain tumor are divided into two types such low grade (grade1 and grade2) and high grade (grade3 and grade4) tumor. Low grade brain tumor is called as benign. Similarly, the high grade tumor is also called as malignant. Benign tumor is not cancerous tumor. Hence it doesn't spread other parts of the brains. However the malignant tumor is a cancerous tumor. So it spreads rapidly with indefinite boundaries to other region of the body easily. It leads to immediate death.¹²

Brain MRI image is mainly used to detect the tumor and tumor progress modeling process. This information is mainly used for tumor detection and treatment processes. MRI image gives more information about given medical image than the CT or ultrasound image. MRI image provides detailed information about brain structure and anomaly detection in brain tissue. Actually, Scholars offered unlike automated methods for brain tumors finding and type cataloging using brain MRI images from the time when it became possible to scan and freight medical images to the computer. Conversely, Neural Networks (NN) and Support Vector Machine (SVM) are the usually used methods for their good enactment over the most recent few years.¹¹ However freshly, Deep Learning (DL) models fixed a stirring trend in machine learning as the subterranean architecture can efficiently represent complex relationships without needing a large number of nodes like in the superficial architectures e.g. K-Nearest Neighbor (KNN) and Support Vector Machine (SVM). Consequently, they grew quickly to become the state of the art in unlike health informatics areas for example medical image analysis, medical informatics and bioinformatics.

II. LITERATURE REVIEW

The main motivation of paper [1] is to introduce a class of robust non-Euclidean distance measures for the original data space to derive new objective function and thus clustering the non-Euclidean structures in data to enhance the robustness of the original clustering algorithms to reduce the noise and outliers.

Paper [2] presents a validation study on statistical non supervised brain tissue classification techniques in magnetic resonance (MR) images. Several image models assuming different hypotheses regarding the intensity distribution model, the spatial model and the number of classes are assessed. The methods are tested on simulated data for which

the classification ground truth is known. Different noise and intensity non uniformities are added to simulate real imaging conditions. No enhancement of the image quality is considered either before or during the classification process.

A variation of fuzzy c-means (FCM) algorithm that provides image clustering is proposed in [3]. The proposed algorithm incorporates the local spatial information and gray level information in a novel fuzzy way. Experiments performed on synthetic and real-world images show that FLICM algorithm is effective and efficient, providing robustness to noisy images.

Paper [4] presents an unsupervised distribution-free change detection approach for synthetic aperture e-radar (SAR) images based on an image fusion strategy and a novel fuzzy clustering algorithm. The image fusion technique is introduced to generate a difference image by using complementary information from a mean-ratio image and a log-ratio image. Experiments on real SAR images show that the image fusion strategy integrates the advantages of the log-ratio operator and the mean-ratio operator and gains a better performance.

In [5], an improved FCM method based on the spatial information is proposed for IR ship target segmentation. The improvements include two parts: 1) adding the nonlocal spatial information based on the ship target and 2) using the spatial shape information of the contour of the ship target to refine the local spatial constraint by Markov random field. In addition, the results of K-means are used to initialize the improved FCM method. Experimental results show that the improved method is effective and performs better than the existing methods, including the existing FCM methods, for segmentation of the IR ship images.

Medical image classification has gained tremendous attention in recent years, and Convolutional Neural Network (CNN) is the most widespread neural network model for image classification problem. CNN is designed to determine features adaptively through back propagation by applying numerous building blocks, such as convolution layers, pooling layers, and fully connected layers. In [6], author mainly focused on developing a CNN model for classifying brain tumors in T1-weighted contrast-enhanced MRI images. The proposed system consists of two significant steps. First, preprocess the images using different image processing techniques and then classify the preprocessed image using CNN. The experiment is conducted on a dataset of 3064 images which contain three types of brain tumor (glioma, meningioma, pituitary). We achieved a high testing accuracy of 94.39%, average precision of 93.33% and an average recall of 93% using our CNN model. The proposed system exhibited satisfying accuracy on the dataset and outperformed many of the prominent existing methods.

The brain tumors, are the most common and aggressive disease, leading to a very short life expectancy in their highest grade. Thus, treatment planning is a key stage to improve the quality of life of patients. Generally, various image techniques such as Computed Tomography (CT), Magnetic Resonance Imaging (MRI) and ultrasound image are used to evaluate the tumor in a brain, lung, liver, breast, prostate...etc. Especially, in this work MRI images are used to diagnose tumor in the brain. However the huge amount of data generated by MRI scan thwarts manual classification of tumor vs non-tumor in a particular time. But it having some limitation (i.e.) accurate quantitative measurements is provided for limited number of images. Hence trusted and automatic classification scheme are essential to prevent the death rate of human. The automatic brain tumor classification is very challenging task in large spatial and structural variability of surrounding region of brain tumor. In [7], automatic brain tumor detection is proposed by using Convolutional Neural Networks (CNN) classification. The deeper architecture design is performed by using small kernels. The weight of the neuron is given as small. Experimental results show that the CNN archives rate of 97.5% accuracy with low complexity and compared with the all other state of arts methods.

III. PROPOSED SYSTEM

The main goal of this research work is to design efficient automatic brain tumor classification with high accuracy, performance and low complexity. In the conventional brain tumor classification is performed by using Fuzzy C Means (FCM) based segmentation, texture and shape feature extraction and SVM and DNN based classification are carried out. The complexity is low. But the computation time is high meanwhile accuracy is low. Further to improve the accuracy and to reduce the computation time, a convolution neural network based classification is introduced in the proposed scheme. Along with this, a chatbot like feature, where user can consult with doctor, is also included in this project.

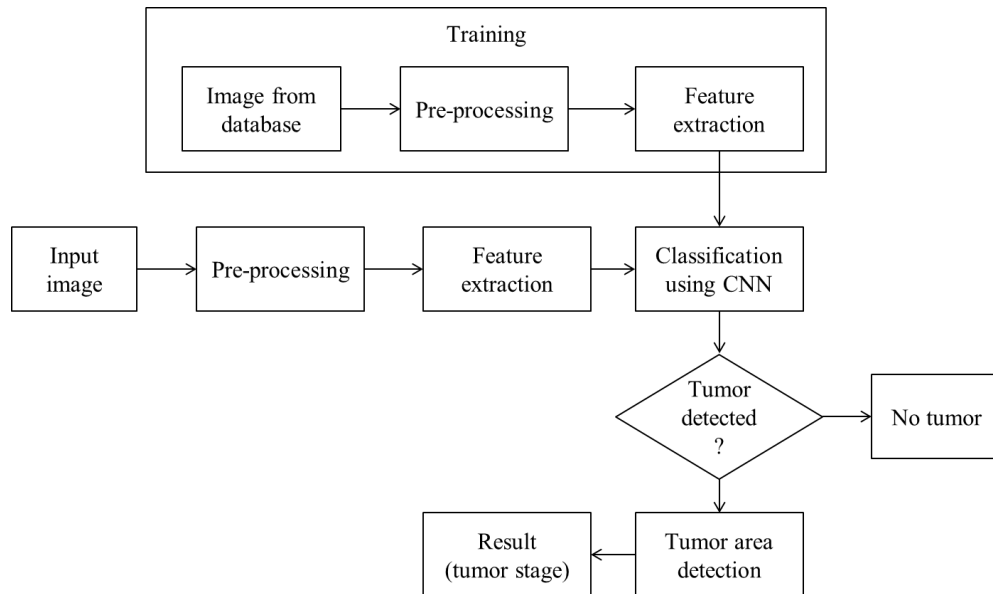


Fig. 1 System Architecture

Input image is image from database (for training) and real time image (brain tumor detection). Pre-processing is a common name for operations with images at the lowest level of abstraction both input and output are intensity images. The aim of pre-processing is an improvement of the image data that suppresses unwanted distortions or enhances some image features important for further processing. Before discussing the extraction of feature points it is necessary to have a measure to compare parts of images.

The extraction and matching of features is based on these measures. Besides the simple point feature a more advanced type of feature is also presented. Feature extraction technique is used to extract the features by keeping as much information as possible from large set of data of image. Dataset is given to train CNN. Classification is performed using CNN. Along with classification, proposed system also perform internet surfing i.e. similar kind of images to query image are surf from internet.

CNN – Algorithm

Artificial Intelligence has been witnessing a monumental growth in bridging the gap between the capabilities of humans and machines. Researchers and enthusiasts alike, work on numerous aspects of the field to make amazing things happen. One of many such areas is the domain of Computer Vision. The agenda for this field is to enable machines to view the world as humans do, perceive it in a similar manner and even use the knowledge for a multitude of tasks such as Image & Video recognition, Image Analysis & Classification, Media Recreation, Recommendation Systems, Natural Language Processing, etc. The advancements in Computer Vision with Deep Learning has been constructed and perfected with time, primarily over one particular algorithm — a **Convolutional Neural Network**.

Over the last decade, tremendous progress has been made in the field of artificial neural networks. Deep-layered convolutional neural networks (CNN) have demonstrated state-of-the-art results on many machine learning problems, especially image recognition tasks. CNN is one of artificial neural networks which have distinctive architectures as shown in Fig. 1; Input data of CNN are usually RGB images (3 channels) or gray-scale images (1 channel). Several convolutional or pooling layers (with or without activation functions) follows the input layer. For classification problems, one or more full connection (FC) layers are often employed. The final layer outputs prediction values (such as posterior probability or likelihood) for K kinds of objects where the input image should be classified in.

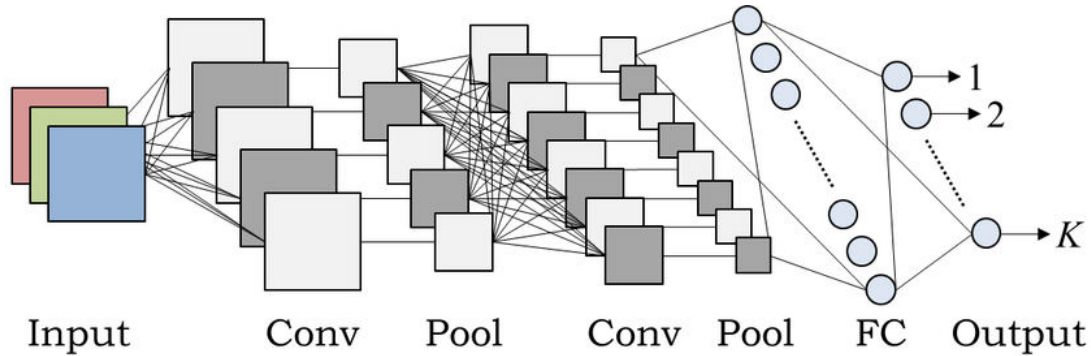


Fig.2 CNN architecture

Each layer of CNN can have a certain activation function which controls amount of output value to propagate its next layer. For intermediate layers, the rectified linear unit (ReLU)

$$f(a_i^l) = \max(0, a_i^l), \quad (1)$$

Note that all $i \in \mathbb{R}$ is a sum of signals received by the i -th unit in the l -th intermediate layer. Meanwhile, for the last layer, the soft-max function is often used to obtain probabilistic outputs.

$$f_k(z) = \frac{\exp(z_k)}{\sum_{\kappa=1}^K \exp(z_\kappa)}, \quad (2)$$

Note that z is a K -dimensional vector where z_k is a sum of signals received by the k -th unit in the last layer. Since the function is non-negative and has the unit sum property ($\sum_k f_k(z) = 1$), the value of f_k implies a class posterior probability that an input data belongs to the k -th class. Therefore, by using the soft-max function in the output layer, CNN can act a role of probability estimators for the object classification problems. As one of the distinctive properties of CNN, they have consecutive multiple feature representations which are automatically organized in their each convolutional layer through the training using given labeled instances.

In spite of this interesting situation, typical dimensionality reduction methods (such as PCA) will visualize each feature representation individually, without regarding the relationships between those consecutive features.

These are the steps used to training the CNN (Convolutional Neural Network).

- Step 1 Upload Dataset
- Step 2 The Input layer
- Step 3 Convolutional layer
- Step 4 Pooling layer
- Step 5 Convolutional layer and Pooling Layer
- Step 6 Dense layer
- Step 7 Logit Layer

Step 1: Upload Dataset

The MNIST dataset is available with scikit for learning in this URL (Unified Resource Locator). We can download it and store it in our downloads. We can upload it with `fetch_mldata`.

Scale the features

Finally, we scale the function with the help of **MinMaxScaler**.

1. **import** numpy as np
2. **import** tensorflow as tf

3. from sklearn.datasets **import** fetch_mldata

Defining the CNN (Convolutional Neural Network)

CNN uses filters on the pixels of any image to learn detailed patterns compared to global patterns with a traditional neural network. To create CNN, we have to define:

1. **A convolutional Layer:** Apply the number of filters to the feature map. After convolution, we need to use a relay activation function to add non-linearity to the network.
2. **Pooling Layer:** The next step after the Convention is to downsampling the maximum facility. The objective is to reduce the mobility of the feature map to prevent overfitting and improve the computation speed. Max pooling is a traditional technique, which splits feature maps into subfields and only holds maximum values.
3. **Fully connected Layers:** All neurons from the past layers are associated with the other next layers. The CNN has classified the label according to the features from convolutional layers and reduced with any pooling layer.

CNN Architecture

- **Convolutional Layer:** It applies 14 5x5 filters (extracting 5x5-pixel sub-regions),
- **Pooling Layer:** This will perform max pooling with a 2x2 filter and stride of 2 (which specifies that pooled regions do not overlap).
- **Convolutional Layer:** It applies 36 5x5 filters, with ReLU activation function
- **Pooling Layer:** Again, performs max Pooling with a 2x2 filter and stride of 2.
- **1,764 neurons**, with the dropout regularization rate of 0.4 (where the probability of 0.4 that any given element will be dropped in training)
- **Dense Layer (Logits Layer):** There are ten neurons, one for each digit target class (0-9).

Important modules to use in creating a CNN:

1. Conv2d (). Construct a two-dimensional convolutional layer with the number of filters, filter kernel size, padding, and activation function like arguments.
2. max_pooling2d (). Construct a two-dimensional pooling layer using the max-pooling algorithm.
3. Dense (). Construct a dense layer with the hidden layers and units.

IV. RESULTS

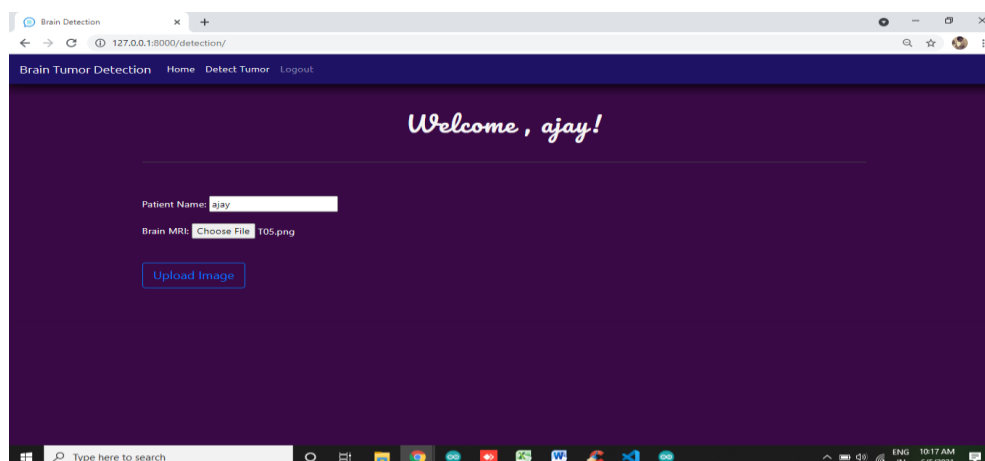


Fig 3 upload image

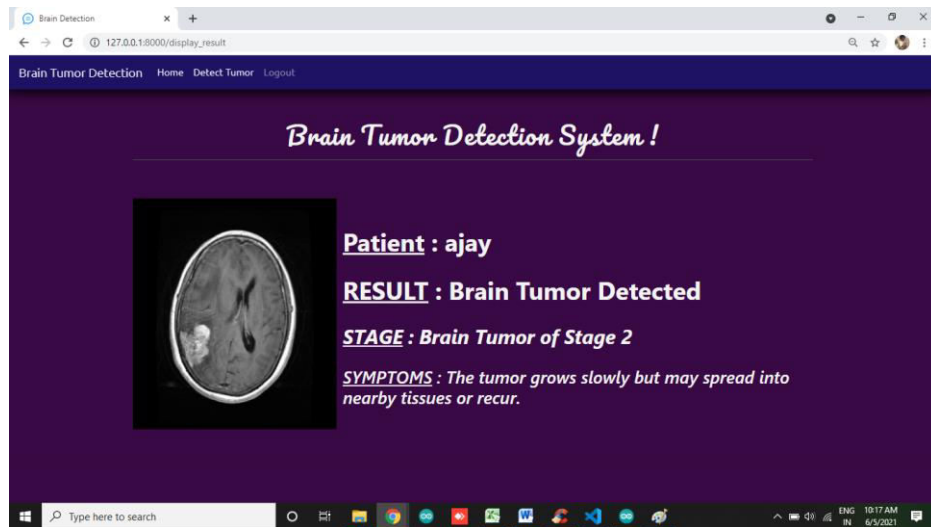


Fig 4 Results tumor Detected

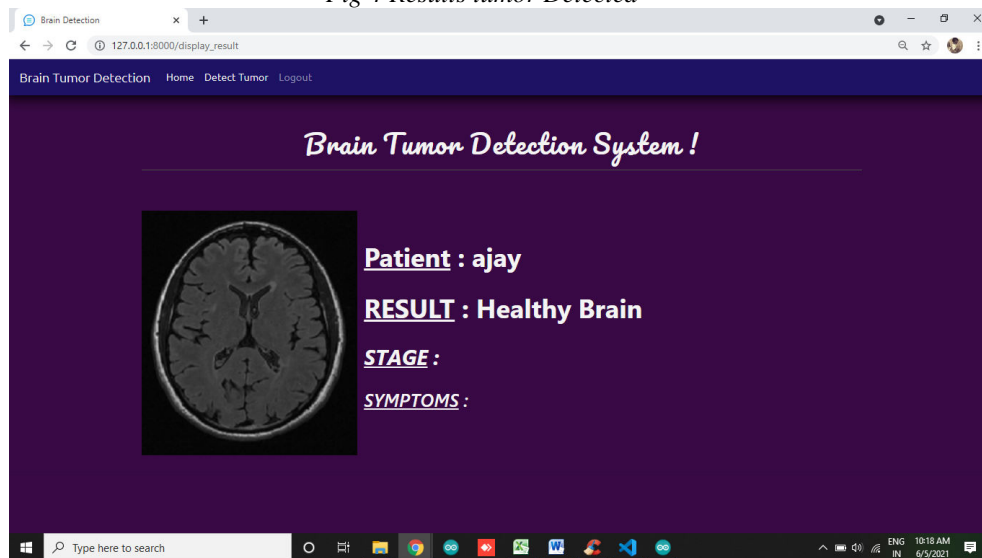


Fig 5 Results – Healthy Brain

V. ANALYSIS

- Total input images = 67
- Correctly Detected = 66
- Wrongly Detected = 1
- Accuracy 98.5 %

Table .1 Caprision with different methods

Sr. No	Method	Parameters		
		Accuracy	Precision	False negative
1	KNN	85%	85%	37 %
2	SNN	95.70 %	96 %	28%
3	Proposed method	98.5%	97.3 %	22%

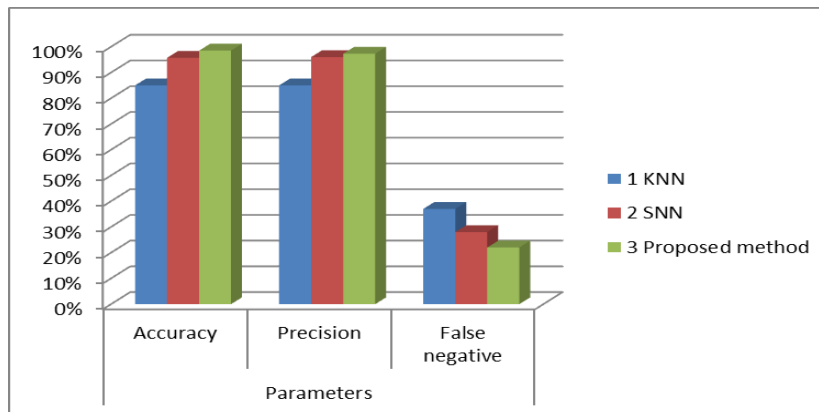


Fig.6. Caprision with different methods

VI. CONCLUSIONS

Brain tumor classification is very crucial in the domain of medical science. In this paper, we concentrated on developing a CNN classifier which classifies tumor. Initially, the proposed system preprocesses the image data. The preprocessing includes filtering images. Then the system classifies the images using the CNN model. Also the classification results are given as tumor or normal brain images. CNN is one of the deep learning methods, which contains sequence of feed forward layers. Also python language is used for implementation.

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