

# BRAIN TUMOR CLASSIFICATION USING CNN

D. P. GAIKWAD<sup>1</sup>, SHUBHAM KUMBHAR<sup>2</sup>, NANDKISHORE NANGRE<sup>3</sup>, SHUBHAM LINGAWAR<sup>4</sup>, ABHISHEK LIMKAR<sup>5</sup>  
<sup>1,2,3,4,5</sup> Department of Computer Engineering, Savitribai Phule Pune University  
<sup>1, 2, 3, 4,5</sup> AISSMS College of Engineering, Pune

**Abstract:** A brain tumor is caused when brain cells divide and grow in an uncontrolled way. There are various types of brain tumor, each fatal in its own way, which is imperative to detect as early as possible. Magnetic Resonance Imaging (MRI) is a broadly used imaging technique to evaluate these tumors, limiting the use of explicit quantitative estimations in the clinical practice. The existing systems for classifying these tumors implemented direct usage of the fully connected network, and use of large filters which eventually increased the computation time and generated unsatisfactory results. Thus, these limitations of the existing systems motivated us to develop an automated and reliable classification system for brain tumor. We propose an automatic classification method based on Convolutional Neural Networks (CNN), by using comparatively small-sized kernels. The use of small kernels allows us to design a profound architecture, besides having a positive effect against over-fitting, given the fewer number of weights in the network. We are trying to implement a better activation function for improving the accuracy of the proposed model. We are investigating the use of intensity normalization as a pre-processing step, which along with data augmentation to be very effective for brain tumor segmentation in MRI images.

**Index Terms** - CNN, Median filter, Leaky Relu, MaxPooling.

## I. INTRODUCTION

Tumour is an uncontrolled growth of tissues in any part of the body. Tumours are of different types and they have different characteristics and different treatment. As it is known, brain tumour is inherently serious and life-threatening because of its character in the limited space of the intracranial cavity (space formed inside the skull)... Generally, CT scan or MRI that is directed into intracranial cavity produces a complete image of brain. This image is visually examined by the physician for detection and classifying brain tumour. However this method of classification resists the accurate determination of tumour. To avoid that, this project uses computer aided method for classification of brain tumour based on Convolution Neural Network (CNN). Convolutional Neural Networks are identical to ordinary Neural Networks. They are generally made up of neurons that have learnable weights and biases. Each neuron receives inputs, performs a dot product and optionally follows it with a non-linearity. In deep learning, a convolutional neural network is a class of deep neural networks, most frequently applied to analyse visual imagery. CNN use a variety of multilayer perceptrons designed to require minimal pre-processing.

The CNN helps to reduce the number of features for training the model without compromising the goodness of features. Before providing image to CNN the image must be filtered and normalized. For filtering the MRI images use of median filter and min-max normalization has been proposed due to its promising results in reducing noise. The pixel values of image is normalized in the range of 0-127. As the number of layers used in this model are more there is problem of vanishing gradient. To avoid vanishing gradient problem, Leaky ReLU activation function is used. In this CNN model 13 layers are used consisting of following layers Conv2D, LeakyReLU, MaxPooling, Conv2D, LeakyReLU, Maxpooling, Conv2D, LeakyReLU, MaxPooling, Flatten, Dense, LeakyReLU, Dense. Softmax activation is used to produce the multiclass output stating whether the tumour is meningioma, glioma or pituitary tumour.

## II. LITERATURE SURVEY

D P Gaikwad, P Abhang, P Bedekar [1] have provided a review for MRI based brain tumor segmentation methods. Firstly, space a brief introduction to brain tumors and imaging modalities. Then, proceeding with the comparison in different imaging modalities. Finally, the brief discussion of the current state is performed and the qualities of different approaches are critically reviewed. Wiest R, Nolte LP, Reyes M.[2] have discussed detail of MRI preprocessing. This paper helped in knowing how easily MRI images get distorted by noise and how to overcome these problems using intensity normalization. Saad ALBAWI et.al., [3] have discussed the functioning of CNN and brief knowledge of how to apply CNN in projects regarding medical imaging.: Madhuri Gundam, and Dimitrios Charalampidis [4] have discussed the effectiveness of the median filter in reducing noise from MRI images.

Dabal Pedamonti [5] have done Comparison of non-linear activation functions for deep neural networks on MNIST classification task. From this paper, we get to know the importance of non-linear activation because of the derivative function. Dipali M. Joshi, Dr.N. K. Rana, V. M. Misra [6] have classified Brain Cancer Using Artificial Neural Network. This paper provided an insight in using CNN for classification of Medical image. B.Suneetha, Dr. A.JhansiRani, V.R Siddhardha [7] have done Survey on Image processing Techniques for Brain Tumour Detection Using Magnetic Resonance Imaging. This paper provided an insight in using appropriate Image processing method for noise reduction from the MRI image. Stefan Bauer, Roland Wiest, Lutz-P Nolte and Mauricio Reyes [8] have done survey of MRI-based medical image analysis for brain tumour studies. This paper provided a brief introduction to brain tumours and imaging of brain tumours.

III. PROPOSED SYSTEM

Convolutional Neural Network has had ground breaking results over the past decade in various fields connected to pattern recognition; from image processing to voice recognition. The most useful facet of CNNs is reducing the range of parameters in ANN. This accomplishment has prompted each researchers and developers to approach larger models in order to solve an advanced task that was not potential with classic ANNs. The foremost necessary assumption regarding issues that are resolved by CNN ought to not have options that are spatially dependent. In different words, for example, in Brain MRI we don't have to concentrate on the tumor we give the whole image as an input to train our model. Another important aspect of CNN, is to obtain abstract features when input propagates toward the deeper layers.

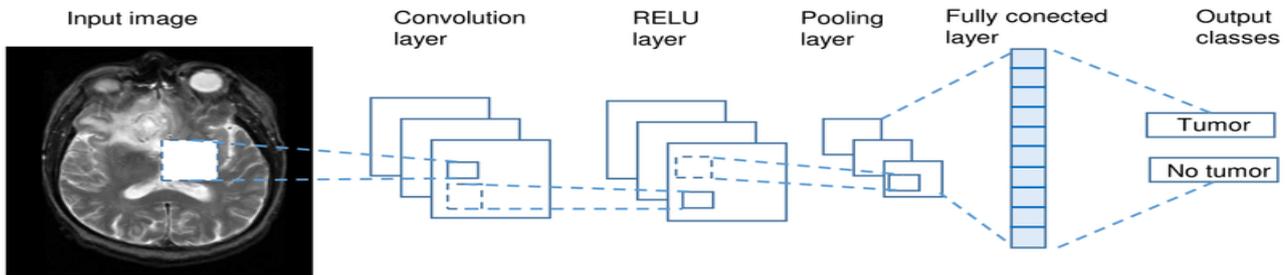


Figure 1: Architecture of CNN for Tumors Detection.

In CNN the convolution is applied on the input image to convolve it resulting in less number of features, we apply filters to do so. We can use kernel of any size like 6X6,3X3,2X2,etc. The kernel is moving in the input, from left to right and from top to bottom, and each one of the values on the kernel is multiplied by the value on the input on the same position. The results obtained by the multiplication are then summed and the local output is generated.

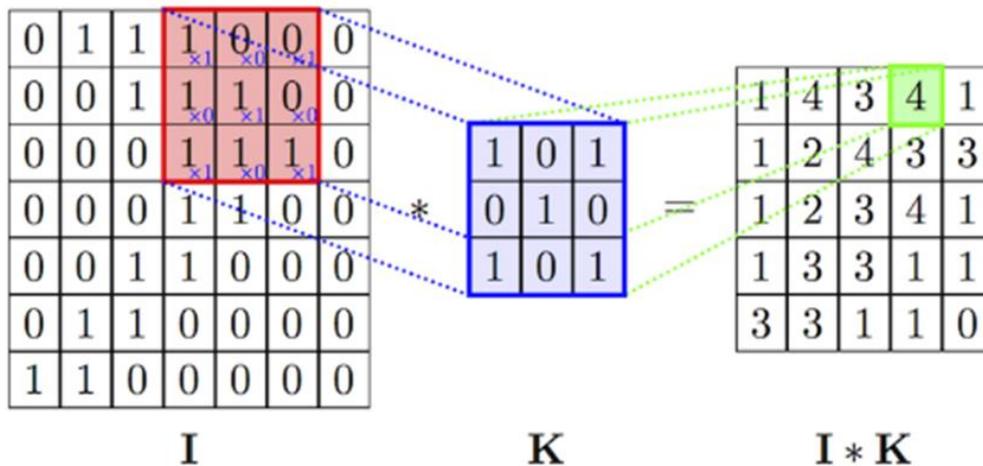


Figure 2: Working of Kernel(3x3)

Activation functions are really important for a Artificial Neural Network to learn and make sense of something really complicated and Network. Their main purpose is to convert an input signal of a node in an A-NN to an output signal. That output signal now is used as an input in the next layer in the stack. Specifically in A-NN we do the sum of products of inputs(X) and their corresponding Weights (W) and apply an Activation function f(x) to it to get the output of that layer and feed it as an input to the next layer. Leaky ReLUs are one attempt to fix the dying ReLU problem. Instead of the function being zero when x is less than 0, a leaky ReLU will instead have a small negative slope (of 0.01, or so).

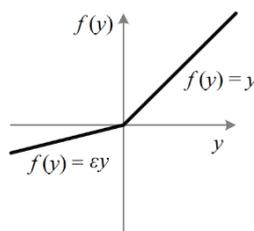


Figure 3. Activation Function Leaky ReLU

It combines spatially nearby features in the feature maps. This combination of possibly redundant features makes the representation more compact and invariant to small image changes, such as insignificant details; it also decreases the computational load of the next stages. To join features it is more common to use max-pooling or average-pooling.

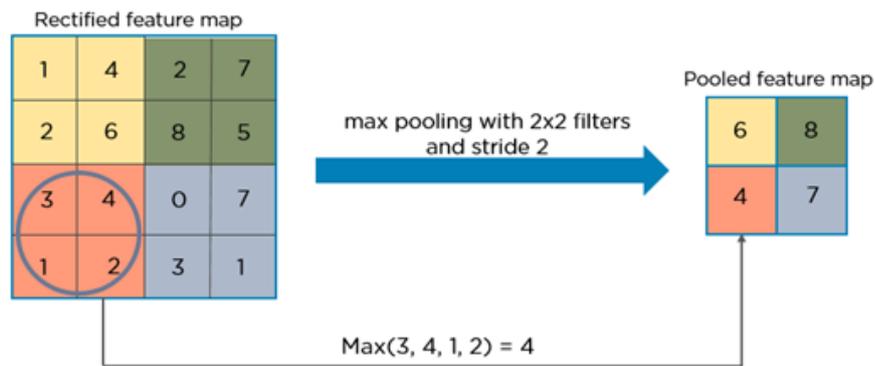


Figure 4. Working of Max-Poling

**Fully Connected Layer:** Fully Connected Layer is used after the convolution of features. Now that our features are reduced we can apply ANN. It can contain many layers and at last we have the output layer.

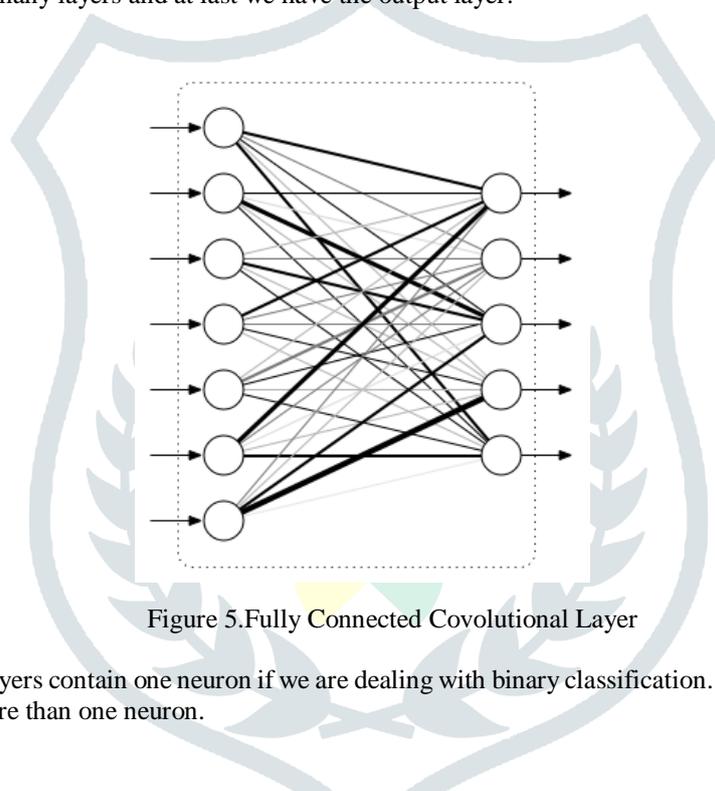


Figure 5. Fully Connected Convolutional Layer

**Output Layer:** The output layers contain one neuron if we are dealing with binary classification. If we are dealing with multiclass classification it can contain more than one neuron.

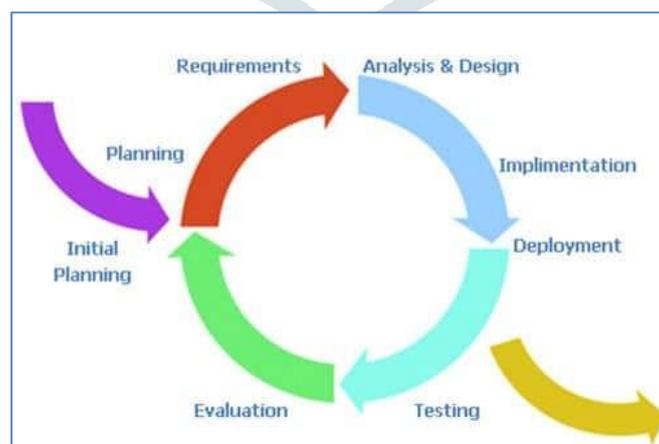


Figure 4: Iterative Design Model

**Iterative Model:** Iterative model start implementation of software functions and iteratively improve the functionality of model until the full system is implemented. In this model planning, requirement, analysis and design, implementation, testing, deployment, evaluation is iteratively implemented to get final system to be ready. In our model CNN is iteratively trained by changing weights of input neuron, or by providing more images to train and then tested on different images.

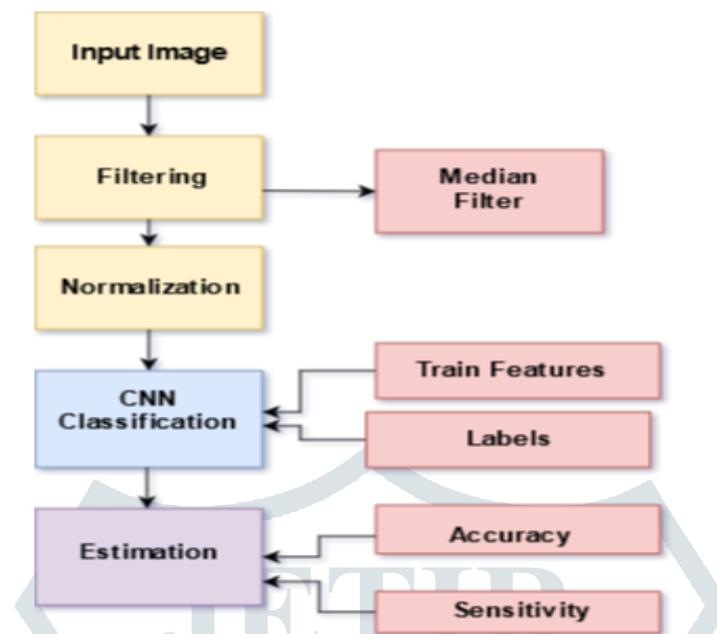


Figure 5 : Flowchart

**3.1 Pre-processing :** MRI images contains noise, these noisy images cannot be given to the CNN classifier for classification. In order to overcome this, median filter is used as it have shown to be effective in removing impulsive noise from images. We have used 3X3 kernel size for this median filter. It is a non-linear digital filtering technique. In this filter technique the 3x3 kernel is mapped to the image and the content of that mapped kernel is sorted in ascending order and the median which is chosen is inserted into the centre pixel of the mapped image by the kernel. Normalization is used to adjust the intensity of pixels in a certain range. In this Max-Min normalization is used and the pixel intensity is adjusted in the range of 0-127.

$$X_i = \frac{X_i - X_{min}}{X_{max} - X_{min}} (newX_{max} - newX_{min}) + newX_{min}$$

Here,  $X_i$  is the current pixel value of the image.  $X_{min}$  is the minimum pixel value and  $X_{max}$  is the maximum pixel value of that image. Now, the pixel value is set in range of 0-127 so  $newMin=0$  and  $newMax=127$ . The new intensity calculated is inserted into  $x_i$ .

**3.2 Convolutional Neural Network :** In this model there are 13 layers, the kernel is of size 6x6, the max\_pooling is of size 2x2. The Total features generated from this model are 6,628,779 which are far less compared to the number of features before applying CNN. The image size reduced from 512x 512 to 64x64 and then it is flattened to 1D feature matrix and is passed to fully connected dense network having 64 neurons. The summary of CNN model is given below.

In the first layer the 512x512 image will be convolved using 32 6x6 kernels by which we got 32 512x512 image matrix which is then passed to second layer where Leaky Relu is applied to the image matrix then the result is passed to layer 3 where max\_polling is done which results in 256x256 image matrix. Like wise we did this 2 more times followed by fully connected dense network and then Softmax activation is used to produce the multiclass output stating whether the tumour is meningioma, glioma, and pituitary tumour.

### 3.3 System Requirement

The database should be scalable and of dynamic nature. Initially the DB should contain MRIs of Timorous and Normal brain. Software Requirements. We will be using the Windows OS. Many of the Programming functions/libraries can be accesses on this platform with great ease. We will be using Python as our coding language as it is one of the latest programming languages in today's market and we can perform large operations with great ease. Also we don't need to write huge lines of code for small operations, there are many inbuilt libraries which can perform these operations, we just need to import the libraries.

3.4 System Architecture

3.4.1 Class Diagram:



Figure 6.Class Diagram

Class diagram is static structure in nature and it is used to model static view of system. It is used to construct executable code of model. In our model Super-class is User Application and Inherited-class is Image Processing. Super class attributes are Spyder IDE, Tinkler, CNN and Operations(Functions) are Load\_Images(),Image-processing() which call sub-class functions like preprocessing(),CNN() and postprocessing().Image i/o is attribute of Inherited-class .

3.4.2 State Machine Diagram:

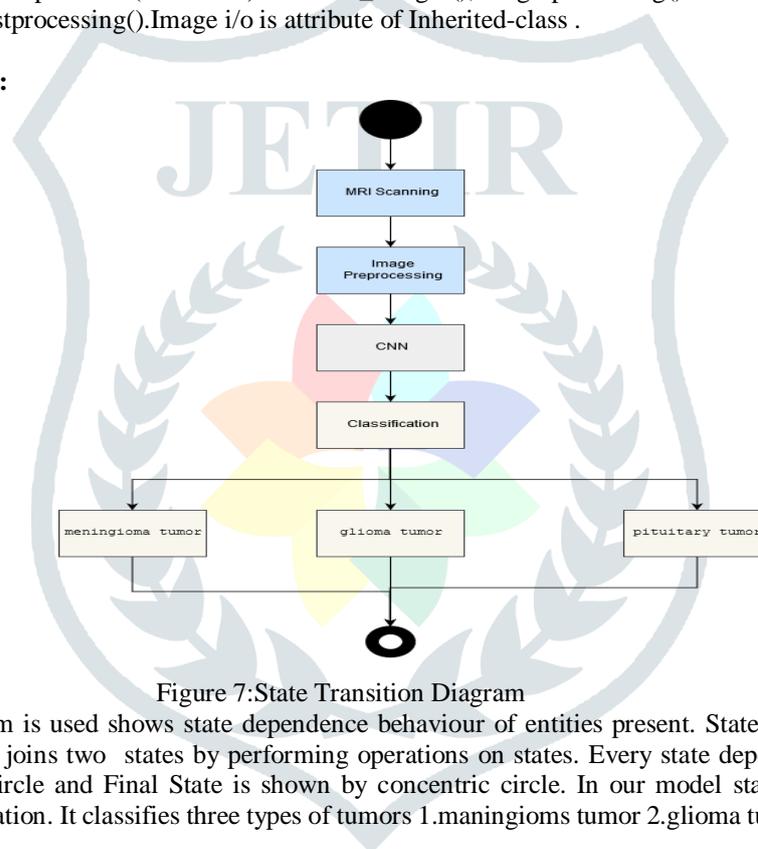


Figure 7:State Transition Diagram

State machine diagram is used shows state dependence behaviour of entities present. State is functions in life cycle of model and state transition line joins two states by performing operations on states. Every state depends on its preceding state. Initial State shown by solid circle and Final State is shown by concentric circle. In our model states are MRI Scanning,Image Preprocessing, CNN, Classification. It classifies three types of tumors 1.meningiomas tumor 2.glioma tumor 3.pituitary tumor. Final state is classified tumor.

3.4.3 C. Use Case Diagram:

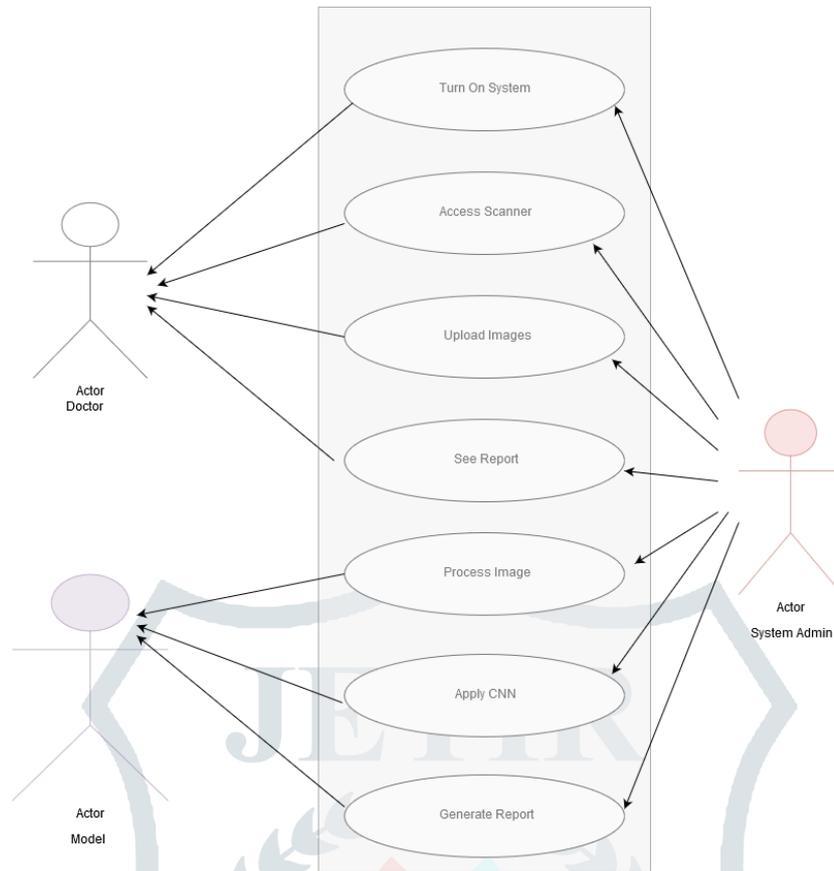


Figure 8: Use Case Diagram

Use Case Diagram:

It shows dynamic behavior of model. Dynamic behavior means systems behavior at runtime. Use case diagram contains Actor, System boundary, use cases, and relationship between actors and use cases. Actors are users, use cases shown by oval, relationship shown by arrow. And boundary shown by rectangle box.

In our model use primary actor is Doctor(user) and secondary actor is system admin(system) and model. use cases are Turn on System, Access Scanner, Upload Image, See Report, Process Image, Apply CNN, Generate Report. Doctors uses system to find tumor in brain by providing scanned MRI image of brain. System executes operations on image and finds whether or not tumor is present or not.

IV. RESULTS AND ANALYSIS

4.1 Results of the system

Describe detailing

Table 4.1: Descriptive Statics

Number of Images	Accuracy
200	0.40
400	0.43
600	0.49
1000	0.55
1700	0.62

As our model is based on Convolutional Neural Network it learn from experience First we took 200 images to train model and got 40 percent accuracy. For 400 images accuracy came 43 percent. For 600 images accuracy came 49 percent, for 1000 images accuracy came 55 percent, for 1700 images accuracy came 62 percent. Accuracy increased as number of images for training is increased.

IV. ACKNOWLEDGMENT

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## V. Conclusion

In summary, we propose a CNN-based method for classification of brain tumors in MRI images. We start by a pre-processing stage consisting of filtering (median filter), max-min normalization. After that, we apply 13 layered CNN consisting of kernels, Leaky ReLU activation function, maxpooling, dense layer and at the end softmax activation function during training to achieve good accuracy. As there is large amount of distributed data CNN reduce data and give the optimal result. In Traditional Algorithms features are extracted manually and then training is done but CNN takes whole image as input and extract features automatically. Model contains various types of layers in which complex computations takes place for this high processors are required. The size and quality of the image needs to be assessed very crucially. If the quality of the image is decreased, then accuracy will get affected and if size is increased, then storage problems may arise. For training as we want to get good prediction accuracy dataset should contain large amount of data this also raise to storage problem.

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