**Paper-1**

**Title**:-**Classification using deep learning neural networks for brain tumors**

**Methodology**:-

The methodology for classification of brain tumor using DNN includes following four main steps.

**step-1 Brain MRIs Dataset acquisition**

There are more than 120 types of brain tumors which differ in origin, location, size, characteristics of the tumor tissues. In this paper three types of malignant brain tumour types are considered :

1. Glioblastoma

2. Sarcoma

3. Metastatic bronchogenic carcinoma

**step-2 Image segmentation using Fuzzy C-means**

Image segmentation is used to separate different normal brain tissue from brain tumor tissue. Fuzzy C-means is used to segment the brain MRI into 5 sections.

**step-3 Feature extraction using discrete wavelet transform (DWT) and reduction using Principle component**

**analysis (PCA) technique**

After segmentation features of the segmented tumor is extracted using discrete wavelet transform (DWT). Methodology utilizes a 3-levels decomposition of Haar wavelet to extract 32\*32 i.e 1024 features for each brain MRI. But this number is not so big compared as to the number of feature maps resulted by the convolution filters of Convolutional Neural Network. Thus the principal components analysis (PCA) is used to approximate the original extracted features with lower dimensional feature vectors.

**Step-4** **Classification using DNN**

After the features are extracted and selected, the classification step using DNN is performed on the resulted feature vector. Classification is performed by using 7-fold cross validation technique for building and training the DNN of 7 hidden layers structure.

**Disadvantages**:-

1.Require more hardware specification and take more time for processing for large size images like(256\*256)

2.Require separate method for segmenation and feature extraction.

**Paper-2**

**Title:-Methods for interpreting and understanding deep neural networks**

In this paper we have studied the problem of interpreting a deep neural network model and explaining its predictions.

Machine learning techniques such as deep neural networkshave become an indispensable tool for a wide range of applica-tions such as image classification, speech recognition, or naturallanguage processing.Techniques for interpreting and understandingwhat the model has learned have therefore become a key ingredient of a robust validation procedure. So interpretability has become more important in applications such as medicine or self-driving car, where the reliance of the model on the correct features mustbe guaranteed.

**1. Interpreting DNN model:-**

This section focuses on the problem of interpreting a conceptlearned by a deep neural network (DNN). A deep neural network (DNN) is an artificial neural network (ANN) with multiple layers between the input and output layers. The DNN finds the correct mathematical manipulation to turn the input into the output, whether it be a linear relationship or a non-linear relationship.As well as DNN is a collection ofneurons organized in a sequence of multiple layers, where neuronsreceive as input the neuron activations from the previous layer, andperform a simple computation.The neurons of the networkjointly implement a complex nonlinear mapping from the input tothe output. This mapping is learned from the data by adapting theweights of each neuron using a technique called error backpropagation.

* 1. Activation Maximization

Activation maximization is an analysis framework that searches for an input pattern that produces a maximum model response for a quantity of interest .

**2. Explaining DNN decisions**

In this section, we take input for a given data point x, which is used to find representative of a certain concept ω c encoded at the output of the deep neural network (DNN). The output neuron that encodes this concept can be described as a function f ( x ) of the input. Data point x can be viewed as a collection of features ( x i ) di = 1 , and to assign to each of these, a score R i determining how relevant the feature x i is for explaining f ( x ) .

**3.Layer-wise relevance propagation (LRP)**

LRP is a backward propagation technique designed for explanation. The LRP technique is based on conservation principle, where each neuron receives a share of the network output, and redistributes it to its predecessors in equal amount, until the input variables are reached.

**4.Evaluating explanation quality**

Some strategies to systematically and objectively assess the quality of explanations.

4.1. Transfer with a simple task

4.2. Explanation continuity

4.3 Explanation selectivity

4.1 discusses how a simple related task can serve as a proxy for that purpose. 4.2 and 4.3 discuss how to perform such quality assesse-ment by looking analytically at the explanation function and its relation to the prediction.

**6.Applications**

Domains as extraction of domain knowledge, computer-assisted decisions, data filtering, or compliance

1)Model validation

2)Analysis of scientific data

**Paper-3**

**Title:-Visualizing Higher-Layer Feature of a Deep Network**

Only model definitions and the quantitative analyses is not enough, there is also need for qualitative comparisons of the solutions learned by various DNN architectures. In this paper we have studied good qualitative interpretations of high level features represented by such models.

**1.Models**

In this paper we have studied two models. The first model is a Deep Belief Net (DBN).This model is obtained by training and stacking three layers as Restricted Boltzmann Machines (RBM) in a greedy manner. The second model, by Vincent et al. (2008), is the so-called Stacked Denoising Auto-Encoder (SDAE).

**2.Maximizing the activation**

We find the input patterns of bounded norm which maximize the activation of a given hidden unit.Asthe activation function of a unit in the first layer is a linear function of the input, in the case of the first layer, this input pattern is

proportional to the filter itself. The reason behind this idea is that a pattern to which the unit is responding

maximally could be a good first-order representation of what a unit is doing. We can find this for a given unit, the input sample(s) (from either the training or the test set) that give rise to the highest activation of the unit. Activation Maximization is applicable to any network in which we can compute the above gradients.

In this we have studied Sampling from a unit of a Deep Belief Network.

**3. Sampling a Unit**

The activation maximization method produces features and it decides which examples would “fit” these features; the sampling method produces examples and it lets us decide which features these examples have in common.

**Limitations**

one cannot find a simple representation of a higher layer unit as we scale the datasets to larger and larger images i.e DNN cannot process larger size iamges efficiently.