The neural network used in our approach is a feed forward neural network,namely the Convolutional Neural Network(CNN).The Convolution Neural Network (CNN) consists of input layer, convolution layer with activation function as the Rectified Linear Unit (ReLU), pooling layer and fully connected layer. In the convolution layer, the given input image is separated into various small regions. Element wise activation function is carried out in ReLU layer. Pooling layer is optional. We are using it as the pooling layer performs down sampling. In the final layer the fully connected layer is used to generate the class score based on the probability between 0 and 1 due to the sigmoid activation function .The CNN based red lesion classification is divided into two phases ,which are, training and testing phases.In the training phase the images are divided into different categories by using label names - “Lesion” and “Normal”. In the training phase, preprocessing, feature extraction and classification with Loss function is performed to make a prediction model. In the preprocessing image resizing is applied to regularise the size of all the images and to enhance the images if required. Finally, the convolution neural network is used for automatic red lesion classification. The brain image dataset used in the approach is the Red Lesion Endoscopy Dataset from The Institute for Systems and Computer Engineering, Technology and Science (INSEC TEC). The loss function is calculated by using gradient descent algorithm.The raw pixel data is mapped with class scores by using a score function. The quality of a particular set of parameters is measured by loss function. It is based on how well the induced scores approved with the ground truth labels in the training data. The loss function calculation is very important to improve the accuracy. If the loss function is high, when the accuracy is low. Similarly, the accuracy is high, when the loss function is low. The gradient value is calculated for the loss function to compute gradient descent algorithm. Repeatedly evaluate the gradient value to compute the gradient of loss function.

In our CNN ,we use a 16 layer network with 6 Convolution layers of kernel size varying as - 8,16,32,64,128 and 256 ,that identify the multiscale features ,the max pooling layers are used after each convolution layer to provide translation invariance and to reduce the computational cost by reducing the number of parameters.The ‘ReLU’ activation function is used for the signal transferring between the layers.After the convolution layers ,the parameters are passed onto 3 fully connected layers of kernel sizes - 512 , 256 and 128 and then onto the final fully connected layer with sigmoid activation function for making the final classification.

The binary_crossentropy loss function or the log loss function is used to evaluate the model performance:

$$H_p(q) = -\frac{1}{N}\sum_{i=1}^{N} y_i \cdot log(p(y_i)) + (1 - y_i) \cdot log(1 - p(y_i))$$

Here ,N is the total number of data points,p(yi) is the predicted probability and y is the label (in our case ‘0’ for “lesion” and ‘1’ for “normal”).

During the training phase ,this log loss function is used to provide feedback to the neural network.

In the testing phase the trained CNN is used to iterate over the unlabeled images and predict the class of the image.