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A Hybrid CNN-KNN Model for MRI brain Tumor Classification

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***ABSTRACT---** Women are an equal soul of men by comprises men in her name itself but really they are treated equal among men. There is a broad gap in between past and present centuries. Women are treated poorly on past centuries by getting huge works, asking more dowries and even killing female infant but in present century these has been reduced and crimes are increased more in numbers against women like abducted, murdered, raped and harassed in various ways. This assessment is on women's tracking system which helps them in their safety and security. Although there are n numbers of tracking devices still crimes against women are in an increasing rate. These crimes have to be reduced in an effective ways of implementing versatile tracking system by combining various technologies into a single integrated unit.*

***Keywords—** Audio and Image, GPS, GPRS, GSM, Sensors.*

I. INTRODUCTION

In human body, Brain is one among the most complex organs which functions on billions of cells. Brain tumor arises due to abnormal growth of cells in an uncontrolled manner affecting the normal functionality of the brain activity and destroys the healthy cells. In current studies there are several methods proposed on classification and feature extraction of brain tumors.

In recent years, several automatic or semiautomatic methods have been proposed for diagnosis and classification of brain tumors [4]. For low-level extraction of features Grey Level Co-occurrence Matrix (GLCM) [1] is used commonly. On the other hand to handle with the complex texture of brain tumor, Neural Networks are used for classification problem [2],[3]. To model new complex and nonlinear relationships between the input and output layers, Deep learning (DL) is introduced. An extension of traditional neural networks (NN) is the DL structure formed by addition of extra hidden layers to the network model. In machine learning, hierarchy of features is discussed using DL[4],[5] as a subfield built on demonstrations of multiple levels of learning where the higher levels are defined from the lower levels and aid in describing many higher level features from the same lower level features. DL has gained the researchers interest because of its good performance and turn out to be the best solution in lots of problems for analysis of medical image applications like image denoising [6], segmentation [7],[8], and classification [9].

At present there are various DL architectures and in recent years convolutional neural networks (CNN) [10] is the architecture used that perform complex operations using convolutional filters. For classification of an image, CNNs are the network architectures commonly used for deep learning.

In machine learning algorithms, the simplest one is the K-Nearest-Neighbor (KNN) Classification algorithm [11]. It is a method for classifying images using feature space built on nearest training data. In Training process, the algorithm stores only the labels and feature vectors of the parameters which are required for training of the images. In classification task, the k nearest neighbors is assigned to the unlabeled query point. Then classification of the image is based on its k nearest neighbors labels. If k=1 means the image is classified as the class nearest to it. k has to be chosen an odd integer when there are only two classes. In this paper there are only two classes considered as benign or malignant. Afterwards each image is converted to a vector of fixed-length with real numbers using Euclidean distance as the common distance function for KNN.

In this paper a huge non handcrafted features are extracted using CNN model then various classifier are considered to classify the class of the given MRI brain images. The CNN-KNN model uses advantages of both methods. The advantages of CNN are sparse connectivity among the neurons between successive layers and weights sharing between layers. The KNN classifies the nearest data samples as a class based on similar measures. This CNN-KNN model extracted the salient features automatically and reduce the laborious and time consumption. Hence this proposed model has better performance compare to other models CNN, CNN-Discriminant (CNN-DISCR), CNN-Support Vector Machine (CNN-SVM), CNN-Naïve Bayes (CNN-NB), CNN-ESEMBLE, CNN-TREE.

The work organization is as follows: section II discusses the architecture of the proposed CNN-KNN model and methodology. Section III deals with experimental results and their analysis. In Section IV conclusions are stated.

Performance metrics: In this paper, the proposed CNN-KNN model is evaluated based on performance metrics [5] such as accuracy, recall or sensitivity, precision or specificity, error rate and F1-score. These performance metrics are defined as follows.

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$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} * 100$$

$$Recall\ or\ Sensitivity = \frac{TP}{TP + FN} * 100$$

$$Precision\ or\ Specificity = \frac{TN}{TN + FP} * 100$$

$$Error\ Rate = \frac{FP + FN}{TP + TN + FP + FN}$$

$$F1\ Score = 2 * \frac{Specificity * Sensitivity}{Specificity\ + Sensitivity}$$

Where TP is True Positive (malignant tumor is predicted correctly), TN is True Negative (benign tumor is predicted correctly), FP is False Positive (benign tumor is predicted as malignant tumor wrongly), and FN is False Negative (malignant tumor predicted as benign tumor wrongly).

II. METHODOLOGY & RESULTS

Figure 1 and 2 show the architecture of the hybrid CNN-KNN model, methodology of the proposed model, and its layers. The architecture used in this methodology includes 25 layers out of which 5 are Convolutional layers and the first layer of this model is an input image of $227 * 227 * 3$ dimension with zero center normalization. The second layer in this model is convolutional layer which includes 96 convolutional filter with a size of $11 * 11 * 3$ with stride 4 and zero padding is applied to the input image. Low level features like edges, blobs, shapes, etc are obtained in this stage. A nonlinear activation function, ReLU and cross channel normalization with 5 channels per element are applied to the previous convolutional layer 'conv1'. The model is down sampled by maxpooling layer of $3 * 3$ with stride 2 and zero padding. Till now one convolutional block is discussed. The proposed model has 5 such convolutional bocks. Second convolutional block is similar to the first convolutional block, but convolutional layer is 256 filters of size $5 * 5 * 48$ with stride 1 and padding 2. Third and fourth convolutional blocks are followed with 384 filters size of $3 * 3$ and padding 1. There is no max pooling layer. Fifth convolutional block is similar to first convolutional block except the convolutional filters are 256. Then three fully connected layers are used to connect all the neurons in the layers. 50 percentage dropout layer is connected between fully connected layers to reduce the features to the nest layer. Last but one layer is probability layer softmax to evaluate the probability of class occurrence. In this Classification problem the number of classes are two like benign and malignant. So that the last fully connected layer is modified as two class classification task with parameters like bias learn rate factor and weight learn rate factor.

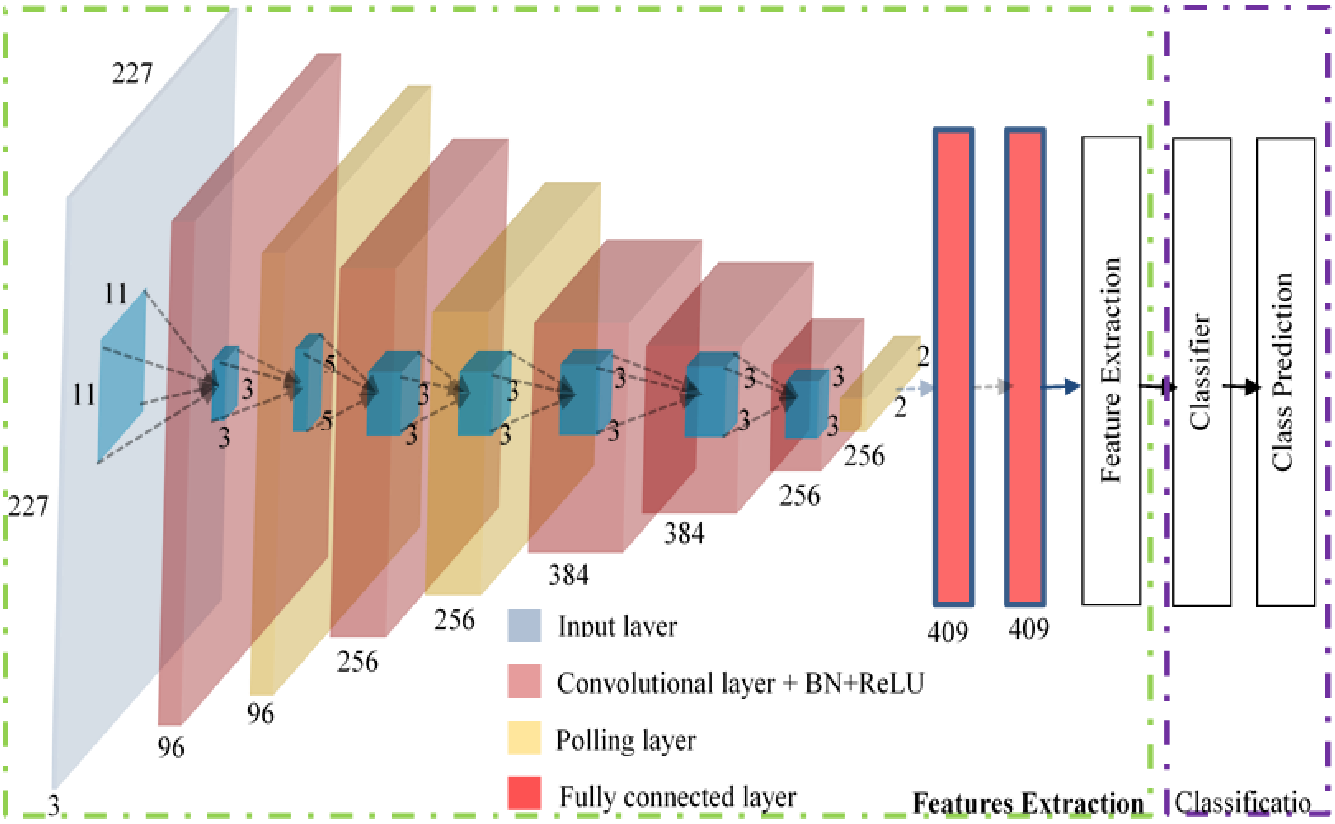

Fig. 1 Block diagram of proposed hybrid model

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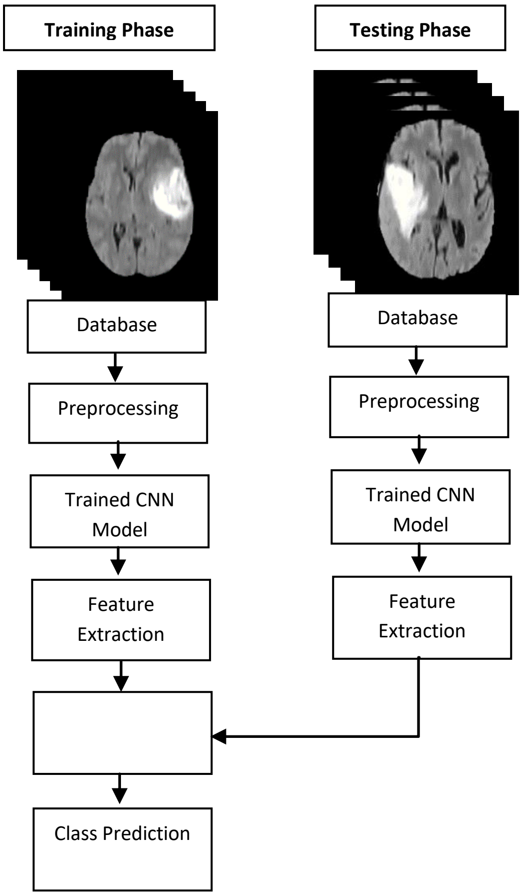

III. EXPERIMENTAL RESULTS

Evolution of proposed model is performed on the image database of BraTS 2015 and executed on Lenovo laptop with Intel i5, 7th generation processor, 8GB DDR4 RAM, and 4GB NVIDIA graphics card. The database BraTS 2015 and BraTS 2017 are a volumetric images which are available in Low Grade Glioma (LGG) i.e. benign and High Grade Glioma (HGG) i.e. malignant. In preprocessing, training data set and testing data set both are processed as required format and then used for training phase and testing phase. Each the image size is $227 * 227 * 3$. The CNN model is trained to training data set of 400 images of both 200 benign images and 200 malignant images. The training options are shown in figure 3. The architecture of the CNN model is described in CNN model architecture and shown in figure 1. At deeper level, high level features are extracted from fully connected layer using activation function. For each image 4096 non hand crafted features are extracted. In this way, 4096 non hand crafted features of 400 images then trained the KNN classifier. On other hand the CNN Model is trained to testing dataset of 240 images of both 120 benign images and 120 malignant images. 4096 non hand crafted features are extracted for each image. Then the classifier predict the class whether the given image is benign or malignant. Finally accuracy of the proposed CNN-KNN is evaluated based on confusion matrix.

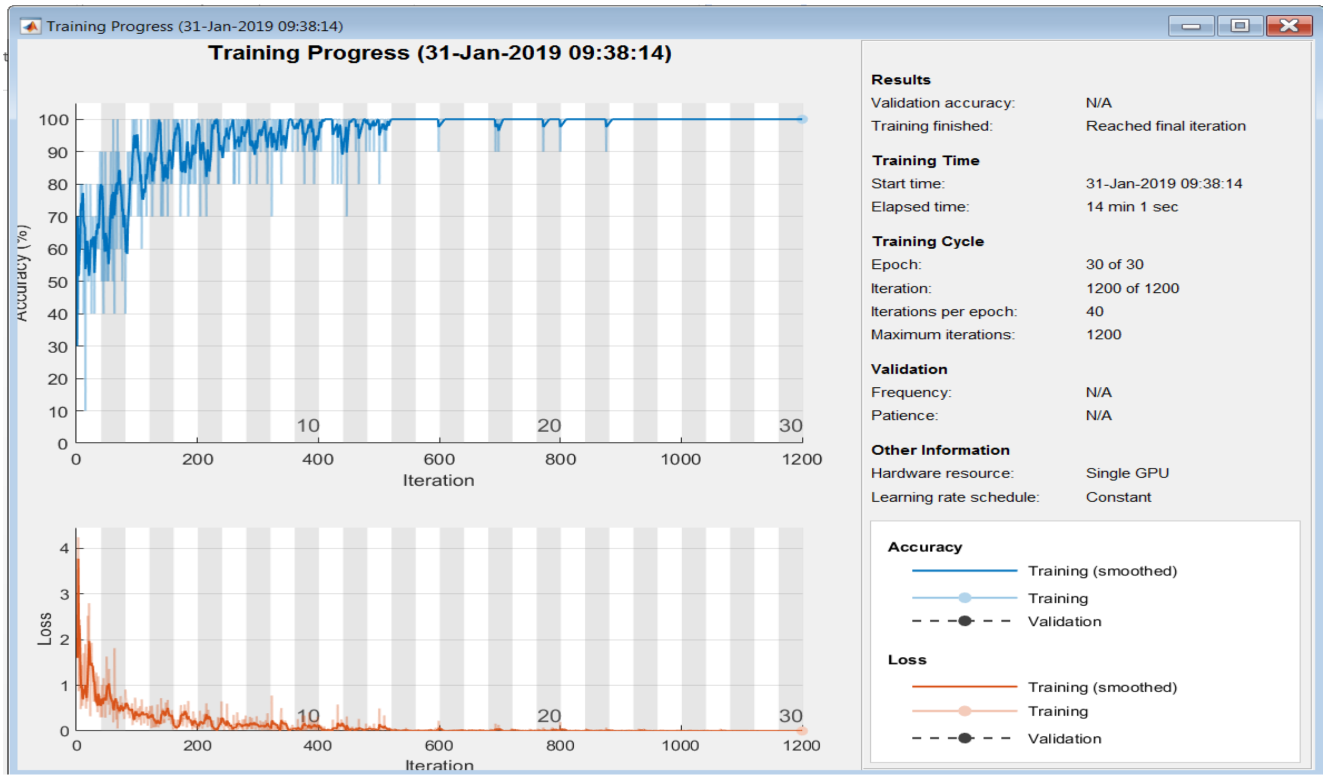

Fig. 3 Training options of CNN-KNN model

The Training options of CNN-KNN model are shown in figure 3. The model is trained using stochastic gradient decent momentum optimizer with 0.0001 learning rate. The model trained for 30 epoch with mini batch size of 20 images. Initially accuracy and loss of the mini batch started with 60 percentage and 0.6910. Finally it reached to 100 percentage and 0.0020.

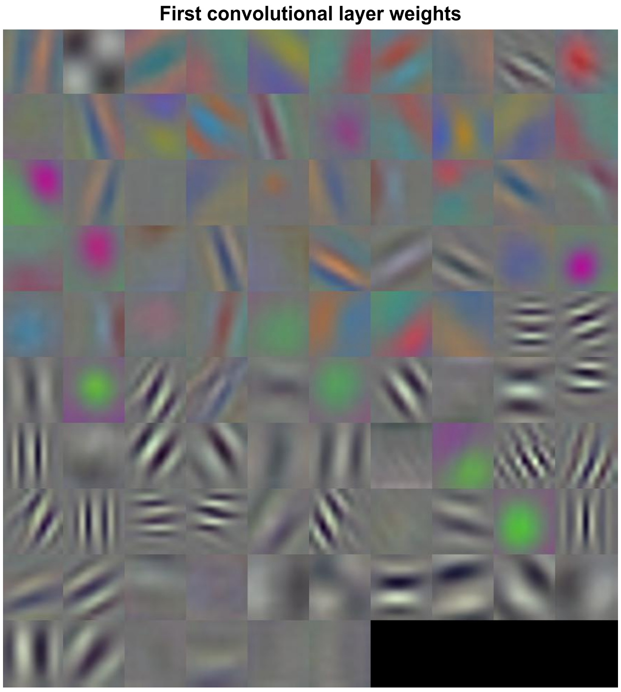

Fig. 4 weights of first convolutional layer

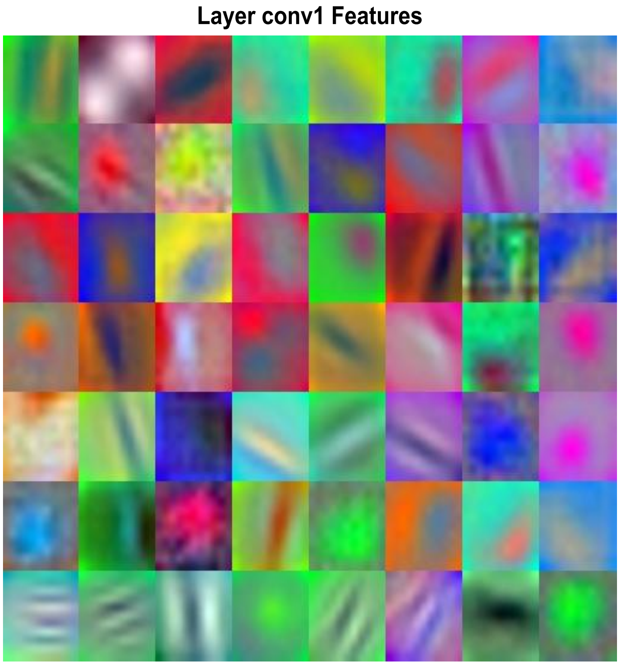

Fig. 5 features of the first convolutional layer

The convolutional filters (96) weights are shown in figure 4. Low level features of the first convolutional layer are shown in figure 5. These features are edges, blobs, and shapes, etc. figure 7 shows the high level features of deeper i.e layer fully connected layer 7. These features are used as input to the classifiers.

Fig. 6 features of the second convolutional layer

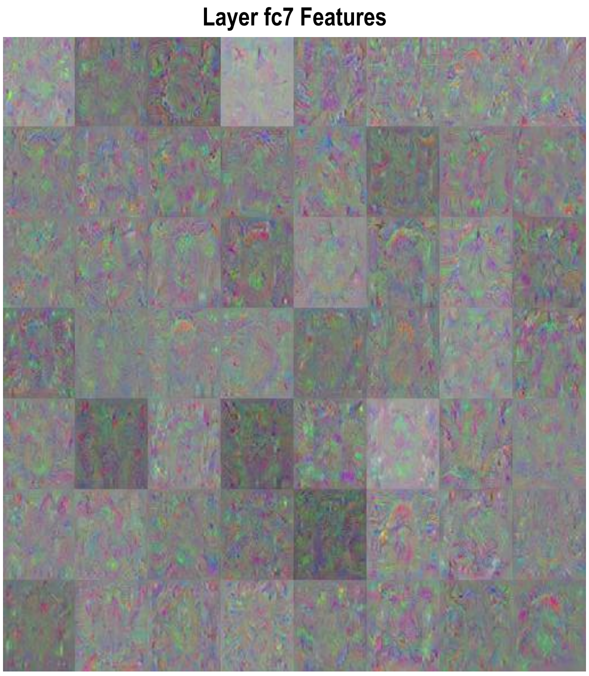

Fig. 7 features of the fully connected (dense) layer

Table I: Confusion matrix of various models.

S.No	Method	TN	FP	FN	TP
1	CNN-KNN	116	4	5	115
2	CNN	117	3	7	113
3	CNN-DISCR	116	4	6	114
4	CNN_SVM	115	5	7	113
5	CNN-NB	106	14	8	112
6	CNN-ENSEMBLE	106	14	9	111
7	CNN-TREE	102	18	11	109

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Table 1 represents confusion matrices of various models like CNN-KNN, CNN, CNN-DISCR (discriminant analysis), CNN-SVM, CNN-NB (naive bayes), CNN-ENSEMBLE, CNN-TREE.

Table II: Performance comparison of various methods.

S. No	Method	Recall	Precision	F1 Score	Error-Rate	Accuracy
1	CNN-KNN	95.83	96.67	96.25	3.7500	96.25
2	CNN	94.17	97.50	95.81	4.1666	95.83
3	CNN-DISCR	95.00	96.67	95.82	4.1666	95.83
4	CNN-SVM	94.17	95.83	94.99	5.0000	95.00
5	CNN-NB	93.33	88.33	90.76	9.1666	90.83
6	CNN-ENSEMBLE	92.50	88.33	90.37	9.5833	90.47
7	CNN-TREE	90.83	85.00	87.82	12.0833	87.97

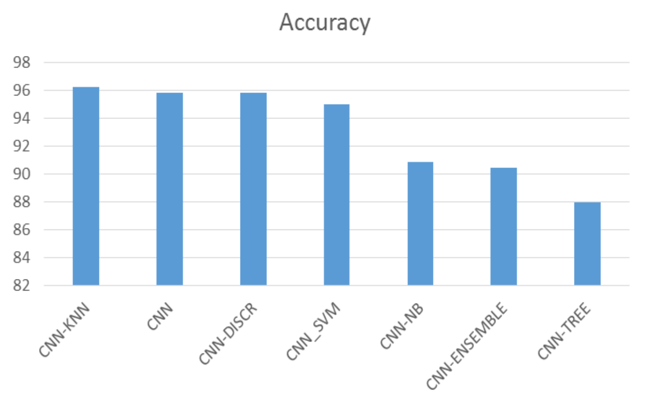

Fig. 8 plot between accuracy and various models

From table 2, the true positive rate (recall or Sensitivity) of the CNN-KNN is more compare to among all other methods. Across the all methods the proposed hybrid methods better performance like accuracy of 96.25 percentage and F1 score of 96.25. With least error rate of 3.75, the CNN-KNN stood in top place.

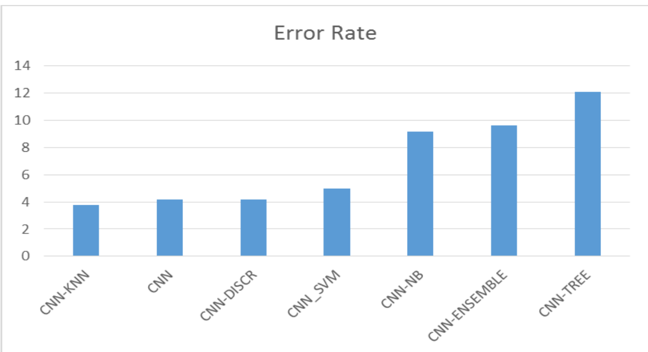

Fig. 9 plot between error rate and various models

Figures from 8 to 10 shows the plots various methods and accuracy, error rate, F-1 sore. From plots it can be concluded that the CNN-KNN model is showing better results.

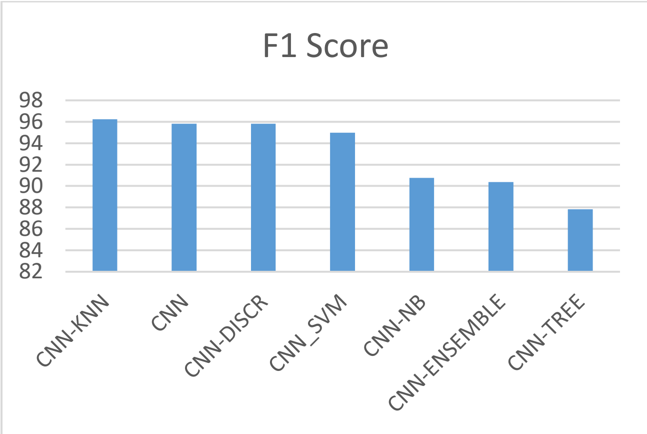

Fig. 10 plot between F1 score and various models

IV. CONCLUSIONS

A Hybrid CNN-KNN model is considered for MRI brain tumor classification problem by training the model using BraTS datasets in this paper. Here, non-hand crafted features are extracted by CNN and applied these features as input to the various classifiers like KNN, CNN, SVM, Discriminant analysis, NB, Ensemble, and Tree to predict the output class. The efficiency and feasibility of the proposed hybrid CNN-KNN model is evaluated based on performance metrics like accuracy, F1 score, and error rate. The results show that this combination of model gives several advantages. From the results this hybrid CNN-KNN model is a promising model for MRI brain tumor classification. Firstly, the model automatically extracted the salient features, which reduce the laborious and time consuming unlike other traditional classifiers as they took more time to extract the acceptable hand crafted features. Secondly, this proposed hybrid CNN-KNN model combined the advantages of CNN and KNN, which are the most successful and popular classifiers for image recognition and classification. Finally, the hybrid model complexity is marginally increased during the decision making process. Among all other models like CNN, CNN-DISCR, CNN-SVM, CNN-NB, CNN-ESEMBLE, and CNN-TREE, the proposed CNN-KNN model provided that the accuracy of 96.25 percentage.

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