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A Novel Brain MRI Image Classification Model using Density Featured Deep Super Learning (DFDSL) Classifier

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ABSTRACT

The brain image automation has improved a lot of features to analyse and predict the infected tissue region in enhanced classification accuracy. For that several methods were focused on the hybridization of algorithms to improve the quality of prediction. This paper proposed a novel model of image classification to predict the abnormality of brain image by using Density Featured Deep Super Learning (DFDSL) Classifier method. This classifies the image features for the combination of 3 set of MRI image types such as, T1-weighted, T2-weighted and FLAIR type of images for individual participants. This combination of image classification can be achieved by using the image registration process using Fractional Fourier Transform with spatial representation for the pre-processed image to identify the matching key points among the image set and merge it into one image data. In this, the image pre-processing was processed by using the Laplacian Cellular Automata Filtering (LCAF) to filter the noise present in the raw image. Then, from that the image can be classified by using the proposed DFDSL classifier. In the DFDSL classifier, it extracts the textural feature parameters of that image which is consider as for the feature learning of classifier. This can identify the clear depth in the image pixel variation which helps to improve the performance of image classifier. The result analysis and the comparison result shows the performance of proposed result compare to other state-of-art methods.

Index Terms— Laplacian Cellular Automata Filtering (LCAF), Image registration, Image classification, Texture features, Density Featured Deep Super Learning (DFDSL) Classifier.

I. INTRODUCTION

IN medical image classification system, most of the prediction techniques focused in the segmentation and classification of abnormal tissue region based on its intensity level and structural features. In that, MRI brain image identification involves a large number of research process to improve the quality of prediction model. Basically, the tumor prediction in the MRI brain image starts with creating a set of rules and several manual conditions to identify the Region of Interest (ROI) of infected tissue are and represent it in colored foreground. The MRI image data contains several categories of image type which can be differentiate by using the weight value of the pixels in that image. These can be listed as T1-Weighted, T2-Weighted, FLAIR image, etc. contains different pattern of image intensity for each type of images. In that, each one contain the information about brain region such as gray matter, white matter, and other tissue region. With the help of these image types, the amount of layers in the brain can be estimated and find the affected level of brain tissue.

The image classification consists of several feature analysis methods based on the supervised and unsupervised learning categories. In that, the supervised learning depends on the level of training / learning provided to it. The unsupervised learning methods involves in identification of nearby pixel variation and found the distance among them. This forms the cluster among the image pixels group and labeled it to represent the differences. Most of the models have both supervised and unsupervised prediction methods to identify the abnormal region of brain MRI image. In that, the segmentation methods involves the unsupervised classification to cluster out the different region in brain image. The supervised classifier extracts the image feature attributes and predict the abnormal level of that image.

In this paper, the supervised classification process was used to identify the abnormality level of brain image for the combination of several MRI image types. As in the previous discussion, there are various MRI image types and each contains various intensity level to represent the brain tissue region. By considering T1, T2 and FLAIR image type, the combination of these images can improve the pixel quality of MRI brain which helps to improve the prediction performance of classification. For that, image registration was used to merge these types of MRI for form it as a single image data to get all the pixel details than by validating single image type. This was implemented by using the Fractional Fourier Transform with the spatial representation of key points. This fused image was then classified by using the novel method of Density Featured Deep Super Learning (DFDSL) Classifier that considered the texture features of image. This is an enhanced technique of Deep Super Learning (DSL) classifier which is integrated with the image density analysis using textural features of image. This type of pattern based classification improves the prediction performance than traditional image classification model.

The main contribution of this paper is

1. To filter the image by using Laplacian Cellular Automata Filtering (LCAF) that remove the additive noise present in the image and enhance the pixel quality.
2. To fuse the T1, T2 and FLAIR type of MRI images using Fractional Fourier Transform with spatial representation method of image registration.
3. To classify the abnormality level of MRI image using proposed DFDSL classifier.
4. To enhance the performance of MRI brain image classification by textural pattern analysis method.

The proposed work in the paper and its detailed description can be organized as following sections: The survey of existing work is presented in section II and proposed work and its algorithm descriptions are discussed in section III. Section IV is discussed about the result and comparative study of overall process with traditional classification methods. Then the discussion about the results of this paper presented in section V. The paper work and its performance is concluded with future enhancement of this work is in section VI.

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II. RELATED WORK

A survey of medical image registration and feature classification methods and their merits with limitations are explained briefly in this section. This section review several papers of existing system and find the suitable methods and steps to enhance the performance of image classification in MRI brain image application.

In the image registration process, there are several methods for the MRI brain image applications. In [1], author proposed a combined method of wavelet-based edge correlation (WEC), speeded up robust features (SURF) feature descriptors and feature point matching to extract the matching points of contours and vessels in the tissue layer. In [2], author proposed a multimodal image registration technique based on the elastodynamics. In this the statistical relationship between the image intensities are evaluated by the gradients of mutual information. This forms the elastodynamics in image processing. In [3, 4], the time complexity for CT angiography was processed by code optimization and parallel processing technique. With the help of image registration, [5] proposed tumor segmentation and classification using ANFIS classifier. The multifractals based 3D image registration was proposed in [6] that reduces the complexity in finding similarity among image features. A non-rigid image registration was processed by using Demons algorithm in [7]. In [8], author proposed brain image morphing technique based on the image registration method.

The feature representation of an image can be categorized as several methods. In this paper, the texture features are considered for the classification process of MRI image. According to that, [9] proposed Principal Component Analysis (PCA), spatial gray level dependence matrix technique were used for the feature extraction and classify by using the SVM method. The PC will reduce the feature coefficients and also reduce the size of it to reduce the time complexity. In [10], author implemented texture estimation for segmenting the abnormal tissue region from the brain MRI image. The texture helps the segmentation process to identify the clear boundary region of tumor spot. In [11], author presented a survey of texture features in MRI acquisition and reconstruction process using radiomic texture feature error identification. Walsh Hadamard kernel- based texture feature extraction was implemented in [12] for the segmentation of tumor spot in brain MRI image. In [13], author proposed morphological transformation and GLCM based texture feature extraction method to analyse the brain MRI image. This was classified by using the SVM classifier. Texture features and kernel sparse coding were implemented in [14] for tumor spot identification and segmentation. In this, the images are split into patches to form 3×3 matrix and estimate the high intensity for each projections. In [15-20], author proposed a texture classification for MR image using Modified Co-occurrence Histograms of Oriented Gradients (M-CoHOG).

To validate the image feature and to estimate the amount of tumor present in an image, it needs to be classify to identify the severity class of testing image. For the classification process, traditional method of machine learning with feature selection method to enhance the classification accuracy. In that, supervised feature selection is implemented by the combination of Tolerance Rough Set (TRS) and Firefly Algorithm (FA) to select the imperative features in brain tumor in [21-28]. Then to improve the detection performance, biogeography-based optimization (BBO) with Support Vector Machine (SVM) classifier is used in [29]. Also to get the detailed feature band of image, [30] proposed dual tree m-band wavelet transform (DTMBWT) with SVM classifier to define the statistical features of brain image. The classification performance is depends on the feature extraction. In that, [31] presents three feature extraction techniques namely, Gray-Level Co-Occurrence Matrix (GLCM), Local Binary Pattern (LBP) and Histogram of Oriented Gradient (HOG) classified by K-Nearest Neighbor (K-NN). In [32], a hybrid feature extraction technique is proposed by using Discrete Wavelet Transform (DWT) and Bag-of-Words (BoW) for brain MRI image. Further an adaptive firefly backpropagation with neural network is proposed in [33] which implements the kernel principal component analysis (KPCA) feature selection technique. For identifying, detecting, locating and classify the MRI brain, [34] proposed Adaptive Convex Region Contour (ACRC) algorithm with SVM classifier. To improve the classification performance, [35] proposed Particle Swarm Optimization Neural Network (PSONN) with Rough Set Theory improves the training performance of neural network for the image pattern.

From the review of different existing methods and its analysis, it shows that the combination of different types of image source will get the clear depth information of the image pixel variation to analyse the affected tissue region and the normal tissue region of image. Also, to improve the classification performance, the textural feature extraction model helps to retrieve the intensity invariant image feature analysis compare to traditional geometrical feature extraction or by the statistical feature data. From these survey, the paper work focused on the image registration before classification process and perform textural feature extraction in Deep Super Learning Classifier model to form Density Featured Deep Super Learning (DFDSL) algorithm. The detailed description about the proposed work are in following sections.

III. PROPOSED WORK

The overall concept of the paper work carries the proposed novel classification algorithm of DFDSL method. Compare to the other classification method in MRI brain image application, this embedded with the textural feature extraction model that internally enhanced the classification performance to predict the tumor affected image. From the reference of Convolutional Neural Network (CNN) classification method, this splits the image into cells and update the feature learning process based on the convolutional feature arrangement. Then from that feature extraction, the neuron networks were arranged and classify the label of image. In accordance with that classification model, the Deep Super Learning classifier splits the image into several individual cells and extracts the feature vector to form the network layers for estimating the predictive distance among the feature arrangement. In the proposed classifier, to improve the classification performance, the texture feature extraction was integrated to form the density analysis of image feature arrangement which is extracted from the image cells or blocks. This performs better prediction model than the traditional convolution model. The fusion of different type of MRI images enhanced the image depth information to extract the texture features of image.

The merits of proposed work is

1. The major advantage of the proposed classifier is the textural pattern validation achieved invariant feature vector for intensity changes.
2. The combination of 3 different image pattern provides more information and clear depth of the brain tissue layers.
3. Cell separated feature learning achieved better performance than the traditional CNN classification model.

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4. The filtering and smoothening of image enhanced the pixel quality which helps to find the edge detail of that image for feature point matching in image registration process.

The proposed work can be segregated into sub modules as,

A. Image Pre-Processing,
B. Image Registration,
C. Tumor Classification.

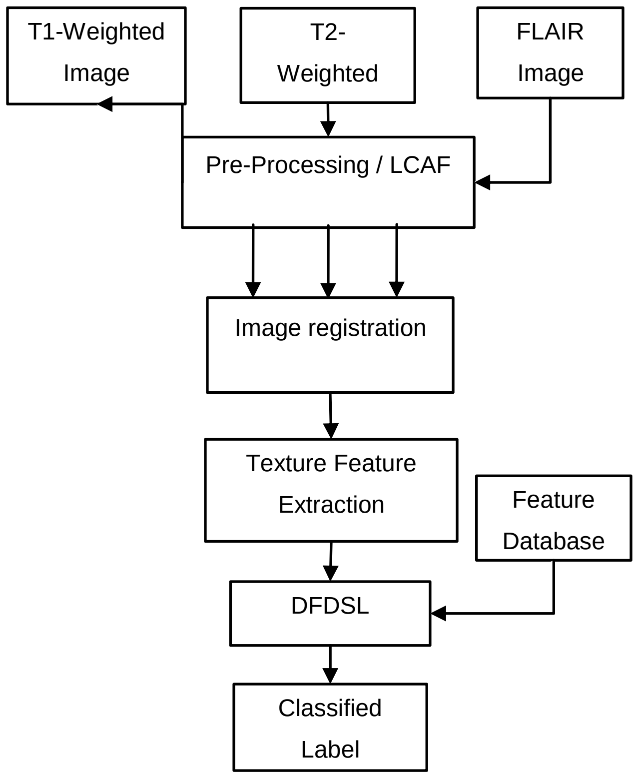

Figure 1: Proposed Block Diagram

A. Image Pre-Processing (LCAF)

The necessity of image pre-processing is to enhance the pixel quality by reducing the noisy pixels present in the image and apply smoothening effect to it. There are several filtering methods that is to reduce the additive noise present in the image based on the distribution model. By considering that, normal distribution was mostly consider as the mapping block to identify the noisy pixel and suppress by the concept of zero mean and unit variance. This paper performs the Laplacian distribution model to filter the Gaussian noise and other instrumental noise which are added while capturing the picture of brain image. The steps and the equations in Laplacian Cellular Automata Filtering (LCAF) is described in the following statements.

The mask size for the filtering process can be in the form of 3×3 or 5×5 matrix size. The sample arrangement and its indexes are shown in the figure 2. For better filtering process, 3×3 mask size is most commonly used for the mapping of distribution.

In that, C_{ij} represents the center pixel of matrix. $N_{\min}$, $N_{\max}$, and N_{std} are the minimum, maximum and standard deviation of boundary pixels of the matrix respectively. By referring the

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center pixel of the matrix or mask of filter coefficients (C_{ij}), this was projected to allover the image cells and identify the difference in pixels by comparing the boundary of window matrix with the reference pixel or center of matrix. The noisy pixel can be evaluate as E_{xy} by the equation 1.

$$E_{xy} = \begin{cases} C_{ij}, & if\,(N_{\min} \geq C_{ij} \geq N_{\max}) \\ 0, & Otherwise \end{cases} \tag{1}$$

i-1, j-1	i, j-1	i+1, j-1
i-1, j	i, j	i+1, j
i-1, j+1	i, j+1	i+1, j+1

(a) 3×3

i-2, j-2	i-1, j-2	i, j-2	i+1, j-2	i+2, j-2
i-2, j-1	i-1, j-1	i, j-1	i+1, j-1	i+2, j-1
i-2, j	i-1, j	i, j	i+1, j	i+2, j
i-2, j+1	i-1, j+1	i, j+1	i+1, j+1	i+2, j+1
i-2, j+2	i-1, j+2	i, j+2	i+1, j+2	i+2, j+2

(b) 5×5

Figure 2: Schematic structure of CA

From that identification, the E_{xy} contains the matrix of noisy pixels for the given testing image. In this paper, the cellular automata represents the division of image into several cells and identify the noisy pixel by comparing the boundary of each cells. If the noise gets identified then this can be rectified by applying the Laplacian filter to the affected cell by considering the center pixel of the cell and its neighboring pixels. The Laplacian function can be defined as

$$LOG(x,y) = -\frac{1}{\pi\sigma^4}\left[1 - \frac{x^2+y^2}{2\sigma^2}\right]e^{-\frac{x^2+y^2}{2\sigma^2}} \tag{2}$$

The input image and the filtered output from the proposed LCAF method is shown in the figure 3.

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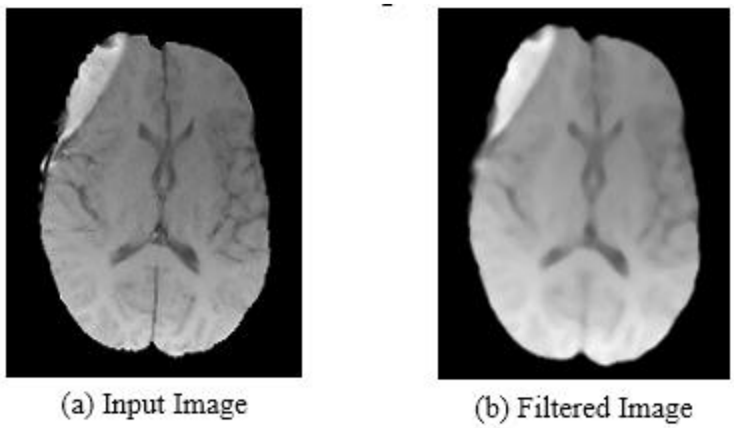

Figure 3: Pre-Processing Result

B. Image Registration using FrFT

Image registration is the process of identifying the matching key points for the given temporal image compared with the reference image and apply rotation and transform according to the key points to merge the set of images into one data. For example, to capture the whole object which is bigger in size and it can't fill in the image capturing image, then this will capture in several angle individually. Then with the edge information, the image set were mapped and form it as a single image. In the proposed work, there are three different MRI brain image source was used for image registration process to represent the whole brain layers and for intensity depth analysis.

For that, Fractional Fourier Transform (FRFT) was used to extract the matching key points for merging the MRI image set. Let, the testing image function can be represent as $f(x,y)$ and the transformed image as $F(u,v)$ [24]. The FRFT for two dimensional image matrix can be represented by

$$F(u,v) = \iint f(x,y) K_{P_1,P_2}(x,y,u,v) dxdy \qquad (3)$$

Where, $K_{P_1,P_2}(x,y,u,v) = K_{P_1}(x,u) K_{P2}(y,v)$

By consider (x, y) as 't' and (u, v) as 'r', the image rotation parameter 'R' will be added along with the parameter 't' due to the change of rotation in function from f(t) to g(t). This can be represented as

$$F(r) = \iint f(Rt) K_{P_1,P_2}(Rt,r) dr \qquad (4)$$

Where. $R = \begin{bmatrix} \cos\alpha & -\sin\alpha \\ \sin\alpha & \cos\alpha \end{bmatrix}$

$\therefore F(r) = F(Rr)$

The *f1* and *f2* are considered as the image translation of two image functions. The *f2* is the translated image function for the input of *f1*. This can be represent as

$$f_2(x,y) = f_1(x - x_0, y - y_0) \qquad (5)$$

According to that, the two images $I_1(u,v)$ and $I_2(u,v)$ are the transformed images from the

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FrFT method. The magnitude of the image transform gives out the fused result of these two images which can be represent as

$$MI_2(u,v) = MI_1((u - x_0 \cos\alpha), (v - y_0 \cos\beta)) \quad (6)$$

$$MI_2(u,v) = MI_1(u - x_0', v - y_0') \quad (7)$$

Where, $x_0' = x_0 \cos\alpha$ and $y_0' = y_0 \cos\beta$

From the equation (7), MI_2 represents the magnitude of transformed image that contains the merged result of two images I1 and I2 (T1 and T2 weighted image respectively). Since, the MI_2 is translated replica of MI_1.

The sample result of image registration for the given three image source is shown in figure 4.

In that the I3 (FLAIR type MRI) is consider as the another source of MRI image that is to transform and merge with the previous registered image result.

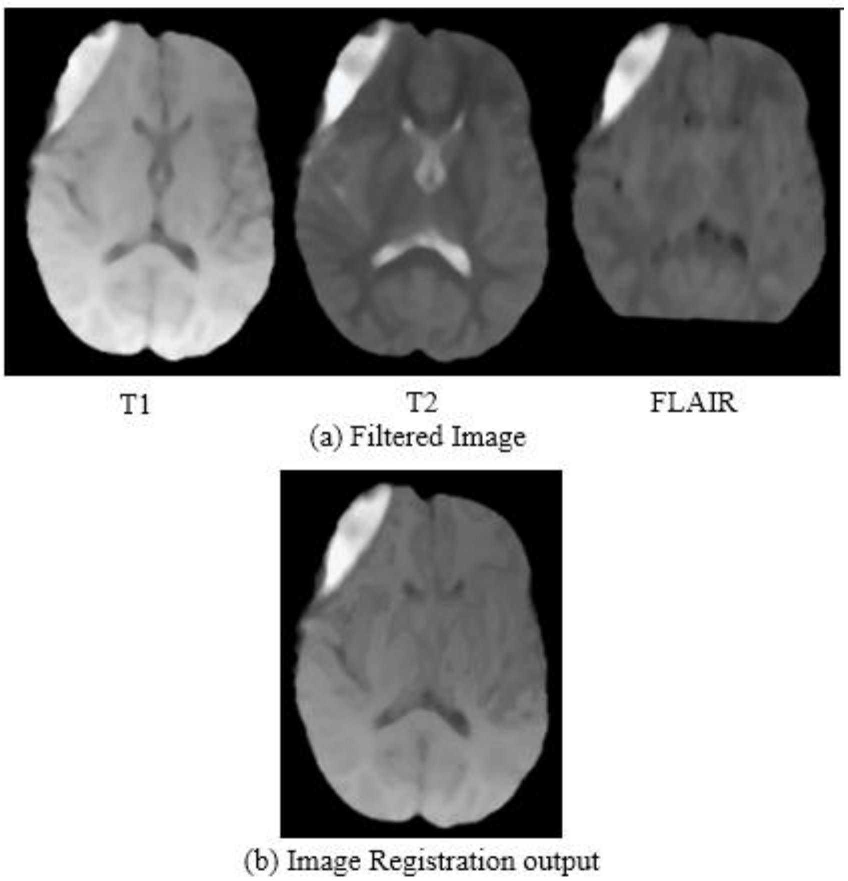

Figure 4: Image Registration Result

C. Tumor Classification using DFDSL

The proposed DFDSL is the enhanced model of traditional DSL classifier. This also works in the basis of neural network technique which differs in the feature analysis and prediction model. The proposed model implements the textural feature analysis model that integrates the texture

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feature attributes to validate the matching pattern with database. The overall Flow diagram of proposed DFDSL classifier is shown in figure 5.

The algorithm 1 describes the step by step procedure for proposed DFDSL classifier.

Algorithm 1: DFDSL classifier algorithm

Image training:
Input: Image Dataset, $\{Y_i\}$
Output: Model Parameter, $\theta = \{W_1, W_2, W_3, B_1, B_2, B_3\}$
For iter = 1 to Max_Iter //Loop run for maximum number of iteration count
Initialize random value for θ by the Gaussian distribution of μ = 0 and σ = 0.001
For i = 1 to n //'n' is the size of training images
For j = 1 to k // 'k' is the number of folds in dataset
For l = 1 to 3 // 3 layers in network
Calculate $F_1(Y) = max(0, W_1 * Y + B_1)$ // W_1 – Filter coefficient for 'Y' image and B_1 – Bias vector for network 1.
Calculate $F_2(Y) = max(0, W_2 * F_1(Y) + B_2)$ // W_2 – Filter coefficient for texture function '$F_1(Y)$' and B_2 – Bias vector for network 2.
Calculate $F_3(Y) = W_3 * F_2(Y) + B_3$ // W_3 – Filter coefficient for texture function'$F_2(Y)$' and B_3 – Bias vector for network 3.
End For '*l*'
Calculate $L(\theta) = \frac{1}{n}\sum_{x=1}^{n} \|F(Y_x; \theta) - Y_x\|$ //Find the distance vector between image sets.
If $L(\theta) < \varepsilon$, then // ε is parameter closed to zero
Calculate $\Delta_{(i+1)} = 0.9 \times \Delta_i + \mu \times \partial L / \partial W_i^l$ // Difference in each iteration
Calculate $W_{i+1}^l = W_i^l + \Delta_{(i+1)}$ // Update the neuron weight value
End If
End For '*j*'
End For '*i*'
Get weight value, average probability and its corresponding loss.
If $loss < Prev_{loss}$, then

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Append average probability
Else
Break iteration
End If
End For '*iter*'

Image Testing:
Input: Testing image 'Y'' and Model Parameter, θ
Output: Classified image $F(Y')$ and corresponding label, L
For l = 1 to 3 // 3 layers in network
Calculate $F_1(Y') = max(0, W_1 * Y' + B_1)$
Calculate $F_2(Y') = max(0, W_2 * F_1(Y') + B_2)$
Calculate $F_3(Y') = W_3 * F_2(Y') + B_3$
End For

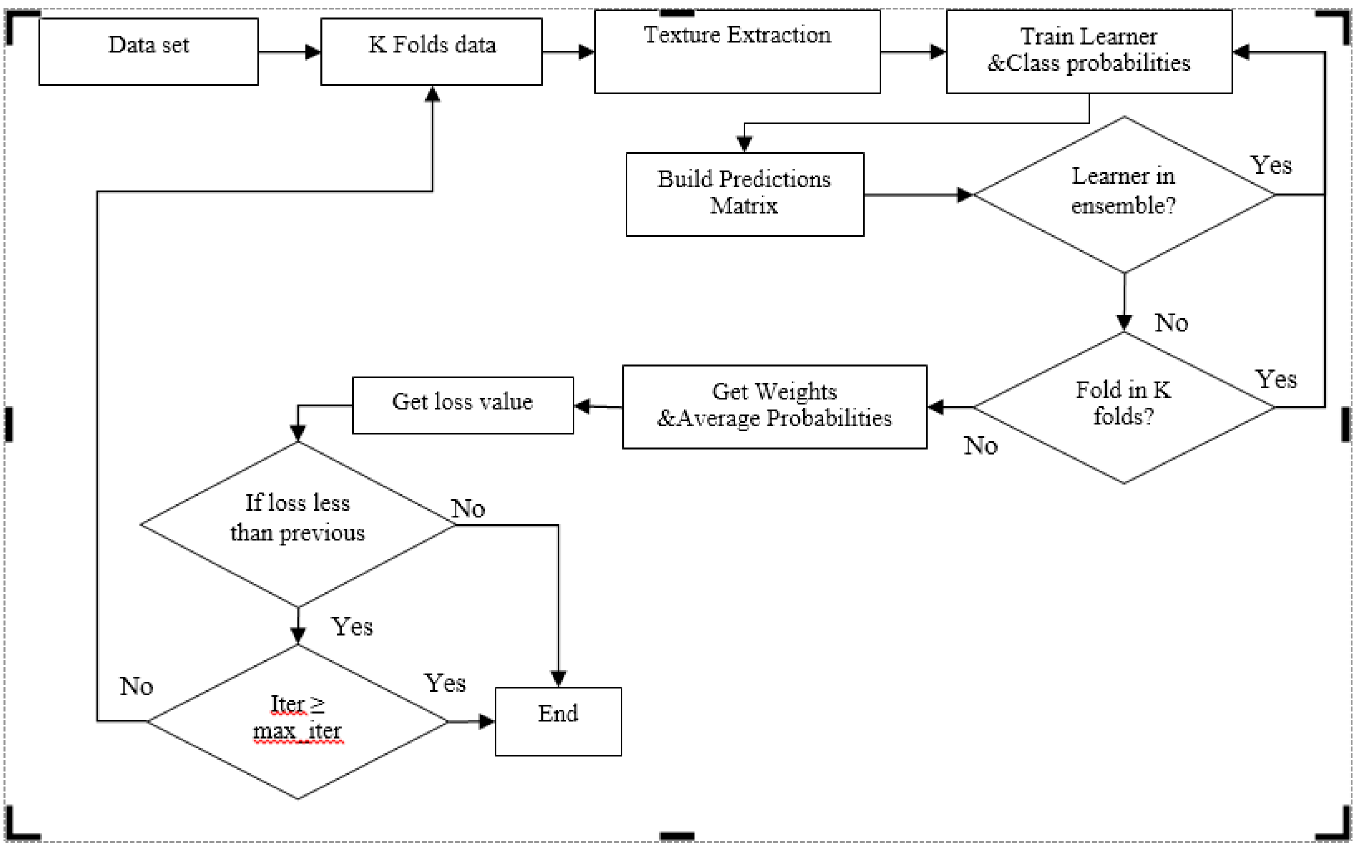

Figure 5: Flow Diagram of DFDSL classifier

From the algorithm table it declares the texture feature extraction for each layer to represent the image block. The figure 6 shows the architecture diagram of proposed Density Featured Deep Super Learning (DFDSL) classifier that represents the flow of classification model for the

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input image data. In that, the feature vector consists of the set of texture features for each block in the image. In this medical image classification application, the labels can be listed as Normal, Benign, Malignant and Metastases for MRI brain image dataset. In this, the training set from overall image dataset can be segmented and processed for 60%, 70%, 80% and 90% of overall MRI images and the remaining set of images are considered as the testing data to validate the classifier performance.

IV. RESULT ANALYSIS

This section evaluates the performance of proposed work and shows the comparison results over other existing classifier model with statistical parameter measures. For that, the BraTS brain image dataset was used for testing the performance of proposed DFDSL classifier. The BraTS image dataset contains several number of image set that has the image source of T1-weighted, T2-weighted and FLAIR type of MRI images of various participants. The database was updated regularly and version maintained to specify the updated image set.

This proposed work is compare with the existing method of long short-term memory (LSTM)-based learning model [25] that was implemented for the same dataset.

The statistical parameters that are considered for the validation of proposed method are Sensitivity, Specificity, Jaccard, Dice Overlap, Precision, Recall, F1-Score, Matthews correlation coefficient (MCC), Error rate Kappa Coefficient and Accuracy.

$$Sensitivity = \frac{TP}{TP + FN} \quad (8)$$

$$Specificity = \frac{TN}{TN + FP} \quad (9)$$

$$Jaccard\_Similarity = \frac{TP}{TP + FN + FP} \quad (10)$$

$$Dice\_Overlap = \frac{2TP}{FP + 2TP + FN} \quad (11)$$

$$\Pr ecision = \frac{TP}{TP + FP} \quad (12)$$

$$\operatorname{Re} call = \frac{TP}{TP + FN} \quad (13)$$

$$F1\_Score = \frac{2 \times \Pr ecision \times \operatorname{Re} call}{\Pr ecision + \operatorname{Re} call} \quad (14)$$

$$MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \quad (15)$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (16)$$

$$Error\_Rate = 1 - Accuracy \quad (17)$$

$$Kappa\_Coeff = \frac{P_o - P_e}{1 - P_e} \quad (18)$$

Where, TP, TN, FP, FN – True Positive, True Negative, False Positive and False Negative

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respectively.

P_o – Relative observed agreement .

P_e – Hypothetical probability of chance agreement.

These can be estimate by the equations (19) and (20).

$$P_o = \frac{TP + TN}{TP + TN + FP + FN} \quad (19)$$

$$P_e = \frac{\left((TP+FP)\times(TP+FN)\right)+\left((TN+FP)\times(TN+FN)\right)}{(TP+TN+FP+FN)^2} \quad (20)$$

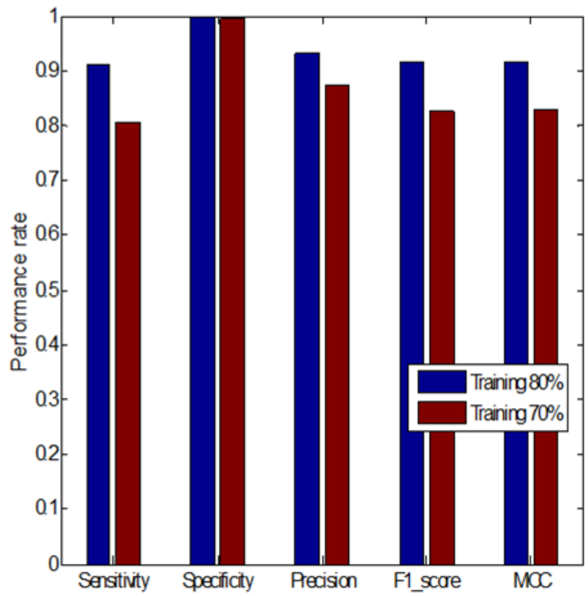

Figure 7: Performance

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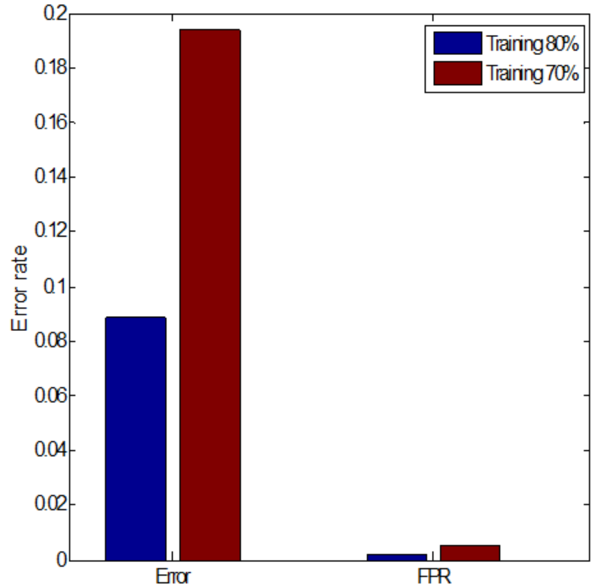

Figure 8: Error rate

The figure 7 and 8 shows the performance measure by the parameters such as Sensitivity, Specificity, Precision, F1-Score, MCC, Error rate and False Rejection Rate (FRR) by comparing the output with ground-truth of the dataset. The bar graphs represents the overall accuracy of the proposed algorithm for two different training set based on the amount of images taken for training and testing process. From the validation of result, the proposed classifier achieved ~98% as maximum. The False Rejection Rate and the error rate represents the amount of false identification from the testing case. In that, the bar chart represents that the proposed classifier reduces the error rate to ~0.01 in value.

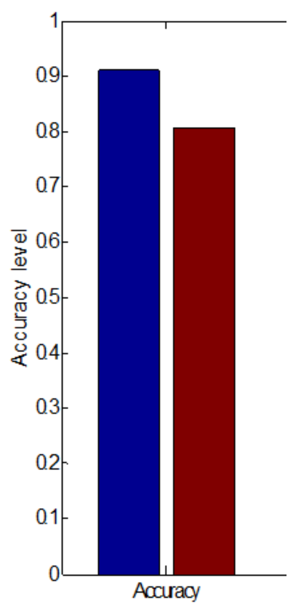

Figure 9: Accuracy chart

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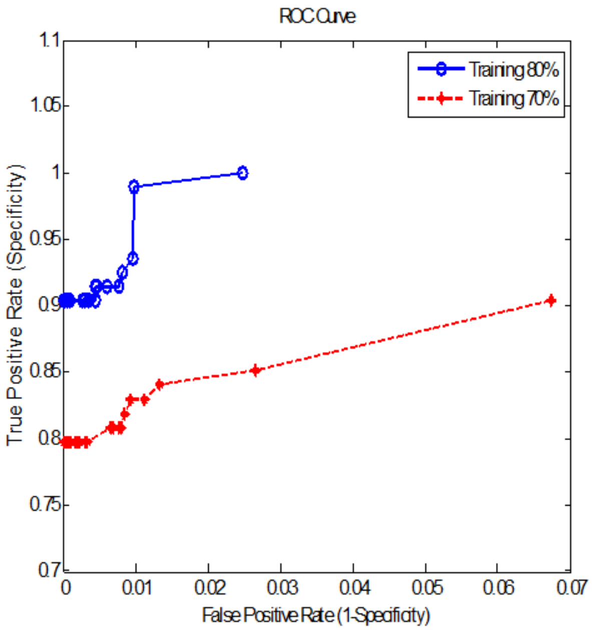

Figure 10: ROC Curve

The figure 9 & 10 shows the bar chat for Accuracy with Kappa Coefficient and the Receiver Operating Curve (ROC) for the training data of 70% and 80% from overall BraTS image dataset respectively. The overall accuracy is depends on the True positive and True negative count from the classifier which is estimated in the confusion matrix. The Receiver Operating Curve represents the amount of True Positive Rate (Sensitivity) for the variation in False Positive Rate (1-Specificity). These parameters are all derived from the confusion matrix which has the data for true positive, true negative, false positive and false negative rate estimated by comparing the predicted result from classifier and actual label from the database.

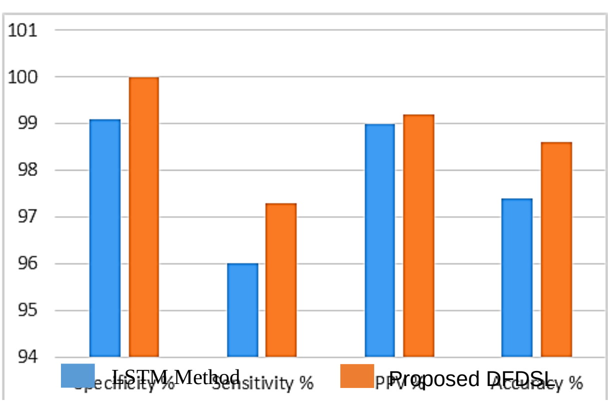

Figure 11: Brain Tumor Classification Result

The bar chart in figure 11 shows the comparison graph of proposed classification result with existing work of [25] for the parameters of Sensitivity, Specificity, PPV and Accuracy in terms of percentage of each. This graph shows that the proposed Depp Super Learning method

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enhanced the performance than the existing system of learning analysis. Also, the Jaccard similarity and the Dice similarity in the figure 12 represents the similarity measurement of classification results compare to the ground-truth of dataset.

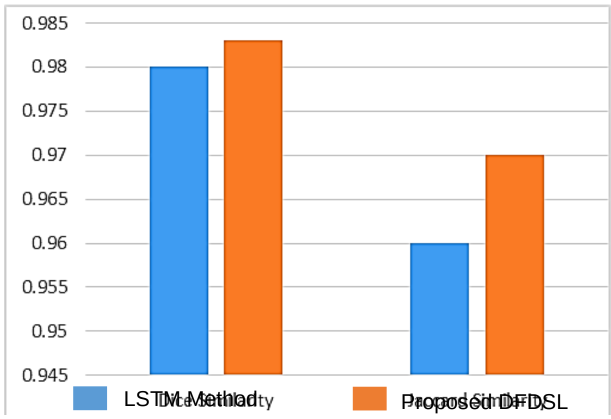

Figure 12: Classification similarity analysis

V. Discussion

The discussion about the proposed work of DFDSL classification method focused on the textural feature analysis process in traditional DSL classification algorithm. From the result analysis, the comparison parameter shows the performance of proposed work over existing algorithm of LSTM based classification model. Here the proposed work also focused on the image quality enhancement by the image registration process for the input of different types of MRI brain image pattern. The merging and the transformed image gives the clear depth in intensity of each layers in the brain MRI input that improves the texture feature extraction in DFDSL classifier.

Generally, the complexity of an algorithm can be evaluate for the two different parameters such as time complexity and space complexity. The time complexity depends on the number of iterations in an algorithm to find the saturated solution and the space complexity id depends on the amount of memory space that is required to compute the intermediate results. The time complexity for the proposed DFDSL classification algorithm can be represent as $O\left(q \times \ln(p)\right)$. In that, the '$q$' represents the total number of iteration cycles that required to find the matching of feature attributes and 'p' be the predicted time taken for each iteration count. In this, the number of iteration count and the time taken is depends on the amount of training for classifier and with the size of dataset. In the testing case, the dataset is divided as 80% training with 20% testing and 70% training with 30% testing to validate the performance of proposed algorithm.

From the result analysis, it shows the overall accuracy of proposed DFDSL achieved ~98% compare to the other traditional classification methods for brain image analysis.

VI. Conclusion and Future enhancement

The paper presented a novel classification algorithm for the MRI brain image classification application. The combination of different source of MRI image like T1-weighted, T2-weighted and FLAIR type images enhanced the visual impact of brain image. Since, the each type of images have different intensity rage to indicate the tissue layer of brain. The registration process manage the intensity different and find the best matching point based on the edge information and pattern of image to merge it into single image data. This type of arrangement gives the clear visualization of each segment of the brain image. In this paper, the texture feature classification was mainly considered as the integration with Deep Super Learning Classifier to form Density Featured Deep Super Learning classifier. This type of texture feature based image analysis improves the performance of classifier than other traditional model of feature analysis. From the result analysis, the overall performance of proposed DFDSL achieved ~1.5% higher accuracy than the existing system of LSTM method.

In future, to further reduce the time complexity and also improve the classification performance, the feature vector can be processed by the optimization algorithm to reduce the size of feature set and selects the best attribute among overall data.

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