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# A Novel Approach to Improve Kernel SVM Classification Algorithm Using Hybrid Approach Based on Texture and Statistical Features of Alzheimer's Stage Using Neuro MR Image

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**Abstract:** Alzheimer's (AD) stage classification is carried on 54 number of T2 weighted Magnetic resonance Images of the subject at different stages. Generating the statistical and textual features are collected by performing segmentation of white matter, gray matter, cerebral spinal fluid, area calculated taken as attributes for the data frame. Classification of the data is carried by Supported vector machines and multilayer perceptron algorithm and compared the result of the classification using Area under curve (AUC), Classification Accuracy (CA), F1, Precision, recall and it is observed that multilayer perceptron with a two Hidden layers having given better 100% classification accuracy kernel SVM gives 96.29% of classification accuracy, by hybrid approach it is possible to increase the kernel SVM performance to 100% classification accuracy.

Keywords: Alzheimer's; Kernel SVM; Multi-layer perception algorithm; GLCM

### I. INTRODUCTION

The Medical image is having more information that needs to analyze and classification of that image is playing a major role in diagnosis disease. Radiologist plays a major role in order to diagnosis the Medical image. But due to the heavy workload a visual impairment, the decision taken by the radiologist may get wrong and it leads the major problem. Due to the urbanization and food habits, peoples are affected with multiple brain disorders [1]. Prevalence and incidence rates of common disorders including epilepsy, stroke, Parkinson's disease and tremors determined through population-based surveys show considerable variation across different regions of the country [2].

As the India is the 2nd largest country in population and facing the problem of elders, the disease named Alzheimer's may affect the person at any time and it makes the person isolated from the society. As per the U.S statistics, most of the death is due to the Alzheimer's the statistics are shown in Figure 1 [3].

As per 2011 Census, India is home to more than 104 million people older than 60 years as per the 2011 Census. This age group, only 8.2% of the population in 2011, is expected to grow dramatically in the coming decades. With demographic ageing comes the problem of dementia. The numbers of persons with dementia double every 5 years of age and so India will have one of the largest numbers of elders with this problem [2].



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#### Figure 1: Percentage of death of all age caused in U.S. between 2000 to 2010 decade.

It is due to the tissue loss and nerve cell death. Over time the brain gets shrink and affect the entire functionality of the brain. The Cortex Shrivels up get damages due to that the person loss thinking, planning and remembering. Shrinking in Hippocampus that play the main role in remembering new memories. Enlargement of ventricles. The early Alzheimer's symptoms start 20 years before diagnosis the primarily affected area is learning memory i.e. Hippocampus of the brain and then affect thinking and planning. As the disease progress, individual may experience the behavioural changes such as recognizing friends and family members. In advance cortex is totally damaged due to plague and tangles. The stages of the brain in Alzheimer's are shown in Figure 2.



Figure 2: Change in the brain at different stages of Alzheimer's.

To know the stage of the Alzheimer's the best method is to take the MRI Image, T1 Weighted and T2 Weighted MRI Images are used to analyze the medical image by observing Gray and White matter volume of the brain, CSF of the brain by observing the shrinkage of the hippocampus, cortex, widening of the ventricles play major role in order to analyze the stage of the Alzheimer's in Table 1. Brain imaging appears based on the magnetic resonance [4].

| T1 Weighted MRI                    | T2 Weighted MRI                   |
|------------------------------------|-----------------------------------|
| CSF Dark                           | CSF Brighter                      |
| White Matter is Brighter than Gray | Gray Matter Brighter White Matter |

#### Table 1: Comparison of T1 and T2 weighted MRI's.

This paper is used to design a hybrid classifier using SVM and MLP classifier it is formatted as introduction to the Alzheimer's disease and how it effect the urban India, in existing techniques it is used to verify the existing machine



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learning systems to make the classification of the data. In proposed system SVM, MLP algorithm is hydride to generate new classifier algorithm and the data is analyzed in using result and conclusion.

### II. EXISTING TECHNIQUES

In order to analyze mild cognitive impairments and normal impairments [5] had used linear regressive mechanism with large network and the performance give the classification with area under curve is 0.87 sensitivity and specificity of 0.85 and 0.80 between mild and normal dementia persons [6], Classification of Alzheimer's Disease of Mild Cognitive Impairment analyzed Using Histogram-Based Analysis [7]. Classifying the Alzheimer's by removing the Nuisance features by using Linear regression [8]. Hippocampus size is used to measure the stage of the Alzheimer's because this is the first thing that effected by Alzheimer's [9] performed the classification based on probabilistic information of the hippocampus volume. Voxel based morphometry classification is used to evaluate the Alzheimer's [10].

#### 2.1 Proposed Method

In this paper the data collected from the MRI Slices are pre-processed by performing segmentation, collecting the texture and statistical parameters from the image along with geometrical parameters. The algorithm is carried as shown in flow diagram (Figure 3).



Figure 3: Algorithm implementation flow chart.

#### 2.1.1 Data base collection:

The algorithm is used to measure the gray matter, white matter, and CSF of the Brain MRI images, using Fiji ImageJ open source software features of the image are extracted, MRI image is collected from http://www.med.harvard.edu/AANLIB, apply the features to wekaopen source software for Machine learning to perform classification.

#### 2.1.2 Enhancing and segmentation of the brain MRI image:

- 1. Stripping the skull from MRI image.
- 2. Segment the Brain MRI image.
- 3. Collect the features of the selected regions.
- 4. Preparing a data set.
- 5. Use the data set to train the classifier.
- 6. Taking other image collecting features and given to the classifier for testing.



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#### 2.1.3 Enhancing and skull stripping:

To get the perfect features it is needed to remove artifacts from the image so that the features extracted should be perfect and useful for perfect classification so, the artifacts of MRI image such as skull and other noise is removed by performing pre-processing techniques. To enhance the image histogram equalization is used that improve the clarity of the image at different regions.

To strip the skull exponential convolution filter K 3X3 size is used the filter kernel of Taylors series is used.

$$e^{x} = 1 + x + \frac{x^{2}}{2!} + \frac{x^{3}}{3!} \pm - - - - - -$$

By performing convolution of input image and kernel the filtered image is generated f(x,y)=g(x,y)\*K(x,y)

| 1 | -1 | 1/2 |
|---|----|-----|
| 1 | 1  | 1   |
| 1 | 1  | 1   |







Figure 4a show the kernel image with x=-1, Figure 4b is the original image and Figure 4c is the image after normalization the resultant image is passed through threshold to binaries the image using the following rule

 $f(x,y) = 1 \text{ if } (x,y) \leq 254$ 

$$f(x, y) = 0$$
 if  $(x, y) = 255$ 



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Figure 5: (a) Threshold image (b) after selecting the major part of the threshold image.

After the threshold erode the image to get Figure 5a and Figure 5b is used as mask to strip the skull of the brain image MRI by performing AND operation on original image with mask function it generate the resultant image of without skull.

 $\begin{array}{l} S(x,y) = g(x,y) \cap f(x,y) \\ S(x,y) = \{g \ / \ f=1 \} \\ S(x,y) = \{0/\ f=0 \} \end{array}$ 



Figure 6: Resultant image after skull stripping.

Skull stripped image (Figure 6) is used for collecting the different regions of the image to perform the classification of the image.

### 2.1.4 Segmentation of gray matter, white matter, CSF:

To segment the image the skull stripped image pass through the thresholding and logical kernel techniques to extract the required regions (Figure 7).

- 1. As input image skull stripped MRI Image is taken.
- 2. Perform and operation between skull stripped image and Binary mask.
- 3. The resultant is the CSF segmented image.
- 4. By performing invert to the mask image and perform AND operation to collect the White and Gray matter of the image.
- 5. Use couture's to select the gray material from the segmented image.
- 6. On performing subtraction of the gray material from the combined image the resultant is the white matter.



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(a)



(**d**)

(e)

Figure 7: (a) Mask of the skull stripped image (b) Image have WM, GM (c) CSF segmented image (d) image have White matter (e) Image with gray matter.

#### Collecting features of the segmented image: 2.1.5

From the segmented image texture features of the image are calculated such as White matter area, gray matter area, CSF area, contrast, correlation, mean, variance, Tendency, difference entropy, dissimilarity, energy, homogeneity of the gray scale co matrix of the segmented image using R programming with radiomics package and EBImage package. The collected features are placed in Excel and convert into CSV file.

#### 2.1.6 **Texture features:**

Input image of  $256 \times 256$  sized gray scale image g(x,y) converted to gray level co-occurrence matrix by comparing the occurrence of the pixels in the particular place.

$$G(x,y) = [g(x,y).g(x+D,y+D)]/g(x,y) = i,g(x+D,y+D) = j$$

i, j are the intensity of the image and based on the image intensity comparing the count is carried and formed a Gray level co-occurrence matrix G.

Matrix is normalized and generated probability based matrix [5] demotes as P with the size of  $256 \times 256$ , statistical features are calculated from the matrix.



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#### 2.1.7 Features calculated:

| Parameter                         | Formula   |  |  |
|-----------------------------------|---|--|--|
| Mean in i direction               | $u_i = \sum_i \sum_j iP(i,j)$   |  |  |
| Mean in j Direction               | $u_j = \sum_i \sum_j i P(i,j)$  |  |  |
| Correlation                       | $\frac{\sum_{i}\sum_{j}(i-uj)P(i,j)}{\sigma_{i}\sigma_{j}}$                               |  |  |
| Homogeneity                       | $\sum_{i}\sum_{j}\frac{P(i,j)}{1+ i+j }$  |  |  |
| Energy                            | $\sum_{i}\sum_{j}P^{2}(i,j)$  |  |  |
| Entropy                           | $-\sum_{i}\sum_{j}P(i,j)\log(p(i,j))$   |  |  |
| Standard deviation in i direction | $\sum_{i}\sum_{j}(I-\mu_{i})^{2}p(I,J)$   |  |  |
| Standard deviation in j direction | $\sum_{i}\sum_{j}(I-\mu_{j})^{2}p(I,J)$   |  |  |
| Angular Secondary Moment          | $\sum_{i}\sum_{j}P(i,j)^{2}$  |  |  |
| Variance                          | $\sum_{i} \sum_{j} (I - \mu_{i})^{2} p(I,J) + \sum_{i} \sum_{j} (I - \mu_{j})^{2} p(I,J)$ |  |  |
| Cluster Shade                     | $\sum_{i}\sum_{j}(i+j-\mu_i-\mu_j)^3p(I,J)$   |  |  |
| Cluster Prominence                | $\sum_{i}\sum_{j}(i+j-\mu_i-\mu_j)^4p(I,J)$   |  |  |
| Inertia                           | $\sum_{i}\sum_{j}(i-j)^{2}p(I,J/\Delta i,\Delta j)$                                       |  |  |
| Dissimilarity                     | $\sum_{i}\sum_{j}(i-j)p(I,J)$   |  |  |



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#### 2.1.8 Feature reduction:

The data set is having 24 attributes both texture and geometrical and the data take more time to make the classification so it need to reduce the attributes so Principle Component analysis (PCA) is used. It uses covariance method. It finds the most covariance data points by keeping the original.

### 2.1.9 Kernel based SVM classifier:

Let the input data  $x \in \{x1, x2, \dots, xN\}$  data points, Support vector machine is used for classifying (-1, 1) classes named as binary classification good clustering accuracy, the linear SVM is not used for Multi class classification so it need to add kernels to provide the required classification [11,12]. Let  $\varphi(xi)$  be the corresponding vectors in attribute space, where,  $\varphi(xj)$  is the implicit function vector mapping and let  $X(xi, xj) = \varphi(xi) \cdot \varphi(xj)$  be the kernel function, implying a dot product in the feature space [11].

There are different kernel functions used for multi class classification X(xi,xj) called the kernel function [13,14]:

- 1. Linear kernel
- 2. Polynomial kernel
- **3.** RBF kernel
- 4. Sigmoid kernel

#### 2.1.10 Multi-layer perception:

It is a supervised classifier and have More than three layers first layer is used to receive the input data and hidden layer is used to perform the manipulation on the input data along with the weights and biasing the resultant pass to the activation function to generate the output the last layer is used to give the classification based on the pre-defined classes.

Let input layer have inputs of:

$$\{x1, x2, x3 - - xN\}$$

The inputs are passed to the hidden layer the node at hidden layer receives the input data along with their weighted values of {W1,W2,W3---WN}, the biasing applied to the hidden layer is B:

$$y = x1W1 + x2W2 + x3W3 + \dots - \dots - xNWN + B$$
$$y = \sum_{n} x_{n}W_{N} + B$$

This output is passed through the activation function the activation function that provide the decision based on the inputs to the hidden node. Most of the cases sigmoid function is used and performed Back Propagation to perform the error minimization using gradient mechanism with the particular moment.

#### 2.1.11 Hybrid KSVM and MLP classifier:

We propose an algorithm that improves the performance of the Kernel SVM by performing Hybrid with Multi-layer perception on PCA Filtered data Frame. Input data is passed through the PCA and it reduce the data set and that data set is passed through the multilayer perception with 2 hidden layer pass that data through the polynomial kernel based SVM algorithm and train it the performance of the algorithm is verified by comparing with test data frame and Let the input data {xi}N is converted into orthogonal features by PCA having {ai} features and those features are given for Hybrid classifier by providing the classes with MLP and those classes are further classified into the classes and the algorithm is tested by the testing data of 44% collected from the original data.

#### III. RESULT AND DISCUSSIONS

MRI sliced images are used to extract the features the image size is  $256 \times 256$  gray scale image are taken (Figure 8).



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Figure 8: Images used for extracting features.

### 3.1 Preparing Data Frame

Collecting Features of the every image and posted in Ms Excel file, save it as Comma separated File with 3 classes, 25 attributes (Figure 9).



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Figure 9: Data frame in CSV format.

### 3.2 Principle Component Analysis

This is used to reduce the data set by removing the un correlated data from the data frame matrix and it select the 3 attributes the selected attributes are shown in the Figure 10.

| 😂 Weka Explorer   |  | - 0 <u>- ×</u>                                |
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| Attribute Evaluator   |  |   |
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Figure 10: Attribute selection by applying PCA.

| Parameters                  | MLP with 2<br>Hidden layer | SVM with Polynomial kernel | Hybrid Classifier |
|-----------------------------|----------------------------|----------------------------|-------------------|
| Classification Accuracy     | 100%                       | 96.2963%                   | 100%              |
| Kappa statistic             | 1                          | 0.9416                     | 1                 |
| Mean absolute error         | 0.024                      | 0.2305                     | 0.1272            |
| Root mean squared error     | 0.039                      | 0.2869                     | 0.1574            |
| Relative absolute error     | 5.5958%                    | 53.7025%                   | 29.6491%          |
| Root relative squared error | 8.4151%                    | 61.951%                    | 33.9789%          |

Table 2: Classifier performance metrics.



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Figure 11: Chart of performance analysis of classifiers.

| Kernel based SVM             | MLP                          | Hybrid SVM with MLP          |
|------------------------------|------------------------------|------------------------------|
| a b c $<$ classified as      | a b c $<$ classified as      | a b c $<$ classified as      |
| 290   b = mild               | 0 11 0   b = mild            | 0 11 0   b = mild            |
| $0\ 0\ 22 \mid c = advanced$ | $0\ 0\ 22 \mid c = advanced$ | $0\ 0\ 22 \mid c = advanced$ |

### Table 3: Confusion matrix of the SVM, MLP and hybrid system.

### 3.3 Data Analysis

From the Confusion Matrix the following data has analyzed for individual classifier it gives the True positive, false positive, precision, Region under curve, PRC Curve. Tables 2-6 shows the comparison of the all three classifiers it is observed that the Hybrid classifier improve the performance of the KSVM by Combining it with MLP.

| Parameter | Normal | Mild  | Advanced |
|-----------|--------|-------|----------|
| TP Rate   | 1      | 0.818 | 1        |
| FP rate   | 0.061  | 0     | 0        |
| Precision | 0.913  | 1     | 1        |
| Recall    | 1      | 0.818 | 1        |
| F-measure | 0.955  | 0.0   | 1        |
| MCC       | 0.926  | 0.884 | 1        |
| ROC Area  | 0.970  | 0.913 | 1        |
| PRC Area  | 0.913  | 0.857 | 1        |

### Table 4: Kernel based SVM data analysis.

| Parameter | Normal | Mild | Advanced |
|-----------|--------|------|----------|
| TP Rate   | 1      | 1    | 1        |
| FP rate   | 0      | 0    | 0        |
| Precision | 1      | 1    | 1        |
| Recall    | 1      | 1    | 1        |
| F-measure | 1      | 1    | 1        |
| MCC       | 1      | 1    | 1        |
| ROC Area  | 1      | 1    | 1        |
| PRC Area  | 1      | 1    | 1        |



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### Table 5: MLP based classification data analysis.

| Parameter | Normal | Mild | Advanced |
|-----------|--------|------|----------|
| TP Rate   | 1      | 1    | 1        |
| FP rate   | 0      | 0    | 0        |
| Precision | 1      | 1    | 1        |
| Recall    | 1      | 1    | 1        |
| F-measure | 1      | 1    | 1        |
| MCC       | 1      | 1    | 1        |
| ROC Area  | 1      | 1    | 1        |
| PRC Area  | 1      | 1    | 1        |

Table 6: Hybrid classifier data analysis.



Figure 12: Performance analysis comparison of kernal based SVM, MLP and hybrid classifier.



Figure 13: Knowledge flow of the KSVM, MLP and proposed hybrid classifier.

By comparing all the above parameter it comes to conclude that the performance of the Hybrid algorithm had a 3.8% constructive improvement in its classification accuracy than KSVM it give the good classification for the data set that we had designed Figures 11-13.



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