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Detection Of Abnormality In Brain Images using Discrete Ridgelet Transform

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Abstract: ***Classification plays a key role for differentiate the brain images as normal and abnormal. Abnormal images mean the brain images contains hematomas (bleeding of blood outside of the blood vessels), tumors (growth of unwanted tissues in blood vessels) etc. Brain Atlas Database is used for proposed work this database comprises normal and abnormal images with different plane like axial, sagittal and coronal with T1&T2 weighted images The present study is used to classify the MRI brain images with kernel SVM incorporated with 3 stages: Preprocessing, Feature extraction, training and classification. In preprocessing grayscale conversion and median filtering is done. Ridgelet Transform is proposed specifically for directional features with line singularities and con-entropy features are extracted by the GLCM. These feature are combined as a feature set and fed input to the kernel support vector machine for training and classification it classifies the brain images with different levels of accuracies. Experimental results show the kernel SVM yields better accuracy compared with existing classifiers.***

***Index Terms*: Brain MRI, Ridgelet transform, GLCM, Classification, Kernel Support Vector Machine.**

I. INTRODUCTION

Brain tumors are the frequent brain disease influence the human brain due to this the brain does not control the various metabolic activities. Brain tumors are leading cause to cancer related deaths especially in children and adults. Imaging modality is important for the analysis of brain tumors these includes CT (Computer Tomography), PET (Positron Emission Tomography), Magnetic Resonance Imaging(MRI) which contains biological data at every moment. With this medical imagery data is used for manual analysis by the physicians but manual analyzation is not accurate for all cases so, computer aided approach(CAD) is employed for automatic and robust radiological assessments with genuine analysis of MRI brain images. RI is very forward, accurate and robust technique used for tumor identification with exact size and finds stages of tumor. It helps to overcome the drawbacks of manual analysis.

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Detection of brain tumors in early stage is used for curing. Mainly, brain tumors are two types benign and malignant. Benign tumors that are unable of spreading beyond the brain that are need not be diagnosed and the spread of these tumors are confined these contains homogenous structure that means does not contains cancer related cells. The other type of tumors are malignant tumors which are called brain cancer and that extends outsides brain and are harmful these are contains heterogeneous structure and contains cancer related cells. In 2017, according to the statistics of American Cancer Society the estimated deaths of brain and nervous system cancers are 9,620 in male and 7,000 in female [1]. In 2018, according to the statistics of Cancer.Net 17,760 adults died with primary cancerous brain and nervous system related tumors in this 9,910 are men and 7,850 are women. Survival rate for the human with brain cancer is 34% for men and 36% for women [2]. Brain cancer occurs in children, the estimated new cases of children in between the age 0- 14 is 3,720 are affected by primary malignant and non-malignant and nervous system related tumors and expected to be diagnosed in 2019. Many advancements are done in Bio- Medical and computer Technology in recent years. These advancements reduce the burden of the physicians for the accurate detections and classifications of the diseases. Several hybrid approaches are used like combination of wavelets with second order statistical features with different classifiers such as k-NN, Adaboost and ANN for classifying the normal and abnormal brain images. But some case it leads misclassification with less accuracy to avoid a novel approach is used with directional features and statistical features with kernel SVM. This paper organized as follows: section II describes related work, Image Database is elucidated in section III, Proposed Methodology is depicted in section IV, in section V experimental results and dissection is described. Conclusion is described in section VI.

II. RELATED WORK

Many techniques are used for the classification of brain MR images with different classifiers such as Fuzzy Clustering Means(FCM), Artificial Neural Networks(ANN), Principle Component Analysis(PCA) and Support Vector Machine(SVM). For improving the classification rate changes made with hybrid classifiers and different features also. Amulya et.al [3] (2016) proposed hybrid features (Speeded Up Robust Features(SURF)+Scale Invariant Feature Transform(SIFT)) with K-Nearest Neighbors(KNN) classifier which achieves the accuracy of 96%,95.4% of sensitivity and 85.7% of specificity.

Astina Minz et.al [4] (2017) proposed adaboost machine learning algorithm for classification brain tumor with GLCM (Gray Level Co-occurrence Matrix) features which gives the accuracy of 89.90%,88.23% sensitivity and 62.5% specificity. Total 50 images are used for used for classification.

Nilesh Bhaskarrao et.al [5] (2018) suggested Berkeley Wavelet Transform(BWT) for efficient segmentation of MR brain images. GLCM features are extracted after segmentation for achieving better accuracy and classification is done by FCM classifier which gives 92.03% accuracy, 91.42% specificity, 92.36% sensitivity.

Mustafa Ismael et.al [6] (2018) proposed novel feature set with the combination of Discrete Wavelet Transform+ Gabor Filter+Gray Level Co-occurrence Matrix(DWT+GF+GLCM) with Back Propagation Neural Network classifier for brain tumor type which achieves 91.9% accuracy,96% specificity and 95.66% sensitivity.

Bobbala Sreedevi et.al [7] (2018) recommended Kernel SVM for hybrid classification and 3-level DWT +GLCM are used to extract textural features and statistical features. Feature reduction is done by the PCA which gives the accuracy of 88.6% for linear kernel ,97.8% sensitivity and 95.3% specificity.

Bhavana Sharma et.al [8] (2018) suggested Computer Tomography(CT) brain images for brain tumor detection and classification with GLCM features. Kernel SVM is proposed for classification of 150 images which gives accuracies of 86% for linear kernel, 98% for (Radial Basis Function) RBF kernel and 90% for Quadratic kernel.

E. J Candes et.al [9] introduced Ridgelets for higher dimensional directional features with line singularities for image processing applications like image denoising, watermarking and image registration.

III. RIDGELET TRANFORM

A Transform for representing the objects with line singularities for sharpen edges called Ridgelet transform introduced by E.J Candes in 1999 [9]. Wavelets are also used for representing the objects with uncommon point singularities but these are not suitable for smoothing and sharpened edges because discontinuity occurs across an edge. In our proposed method Ridgelet Transform(RT) is used to extract the features from sub bands of ridgelet decomposition that means ridgelet coefficients. This Ridgelet Transform are of two types:

1. Continuous Ridgelet Transform(CRT).
2. Discrete Ridgelet Transform(DRT).

Continuous Ridgelet Transform:

The continuous Ridgelet transform with bivariate function f(x) is given as:

$$CR_f(a,b,\theta) = \int_{R^2} \varphi_{a,b,\theta}(x) f(x) dx \qquad (1)$$

For each a >0, b∈ R, θ ∈[0,2Π]

Where $\varphi_{a,b,\theta}(x)$ is the ridgelets bivariate function :$R^2 \rightarrow R^2$ and is given by :

$$\varphi_{a,b,\theta}(x) = a^{-1/2}\left((x_1\cos\theta + x_2 \sin\theta - b)/a \right) \qquad (2)$$

Where φ is the smooth univariate function with sufficient decay. In 2D $x_1\cos\theta + x_2\sin\theta = const$.

The reconstruction formula for continuous ridgelet transform as

$$f(x) = \int_0^{2\Pi}\int_{-\infty}^{\infty}\int_0^{\infty} CR_f(a,b,\theta), \varphi_{a,b,\theta}(x) \frac{da}{a^3} db \frac{d\theta}{4\Pi} \quad (3)$$

Continuous ridgelet transform is similar to the 2D continuous wavelet transform(CWT) except from replacing the point parameters with line parameters.

$$Wavelets : \varphi_{scale_{point-position}}$$

$$Ridgelets : \varphi_{scale_{line-position}}$$

Points and lines related with the radon transform in 2D which means wavelets and ridgelets are linked with the radon transform for collection of point and line integrals. The Radon transform as follows

$$R_f(\theta,t) = \int_{R^2} f(x)\delta(x_1\cos\theta + x_2\sin\theta - t)dx \qquad (4)$$

The ridgelet transform is the application of 1D wavelet transform to the pieces of Radon transform and is denoted as

$$CR_f(a,b,\theta) = \int_{R^2} \varphi_{a,b}(t) R_f(\theta,t)dt \qquad (5)$$

Replacing the 1D WT on radon transform with 2D Fourier transform. Let $F_t(w)$ be the 2D Fourier function f(x) as

$$F(\xi\cos\theta, \xi\sin\theta) = \int_R e^{-j\xi t} R_f(\theta,t)dt \qquad (6)$$

Discrete Ridgelet Transform:

Discrete Ridgelet Transform means total implementation is done in Fourier domain. The block diagram explains the operation DRT in figure 2. The below algorithm explains total process of DRT.

ALGORITHM 1: DRT Applied an images

start
Step1: Take an input Image of square size (equal size).
Step2: Specify the number of levels (scale) for sub band decomposition.
Step3: specify the weather our output is a cell array or vector.
 if md=1
 output is a cell array.
 else
 output is a vector.
Step4: Calculate the size of the image and resize the image with equal size.
Step5: Apply 2D FFT on image.
Step6: Find out the pseudo polar rectangle and represent in Cartesian form.
Step7: Apply 1D IFFT along the radial variable radon space.
Step8: Finally, apply 1D WT for ridgelet coefficients with angle and frequency.
End

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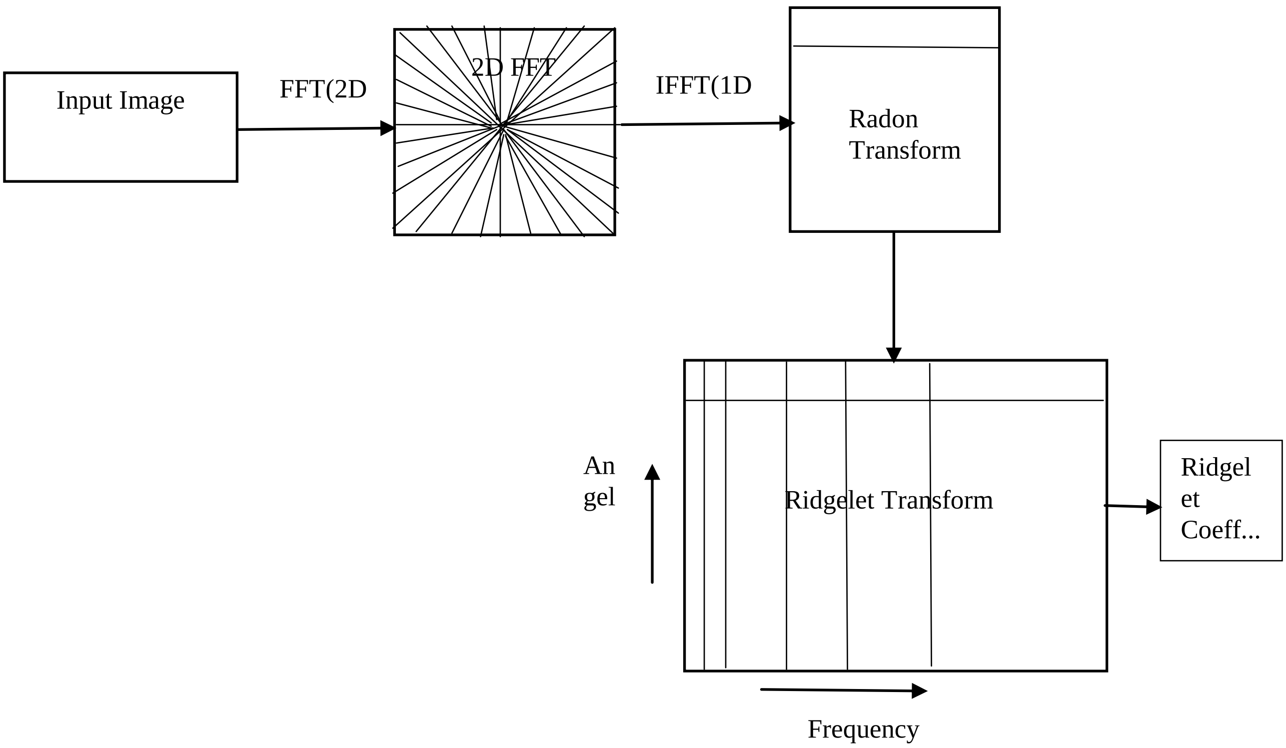
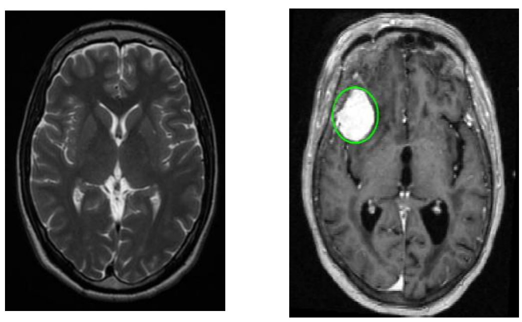


Figure 2: Block Diagram of DRT.

IV. PROPOSED METHODOLOGY

Proposed methodology is explained step by process with block diagram shown in figure 3.

1.Brain MRI Database:
The MRI brain images are taken from the Brain Atlas database [10] which consists of normal and abnormal in fig4. The abnormal images have the diseases like Neoplastic, Cerebrovascular and inflammatory. Total 150 images are taken with the size of 256x256.



(a) (b)

Figure 4: (a) Normal MRI brain image (b) Abnormal MRI brain image.

2.Pre-processing:
In preprocessing stage first check whether the input image is gray scale or not if it is not gray scale image convert the input image into gray scale format and then apply the median filtering for removing the noise present in the input images shown in below fig5.

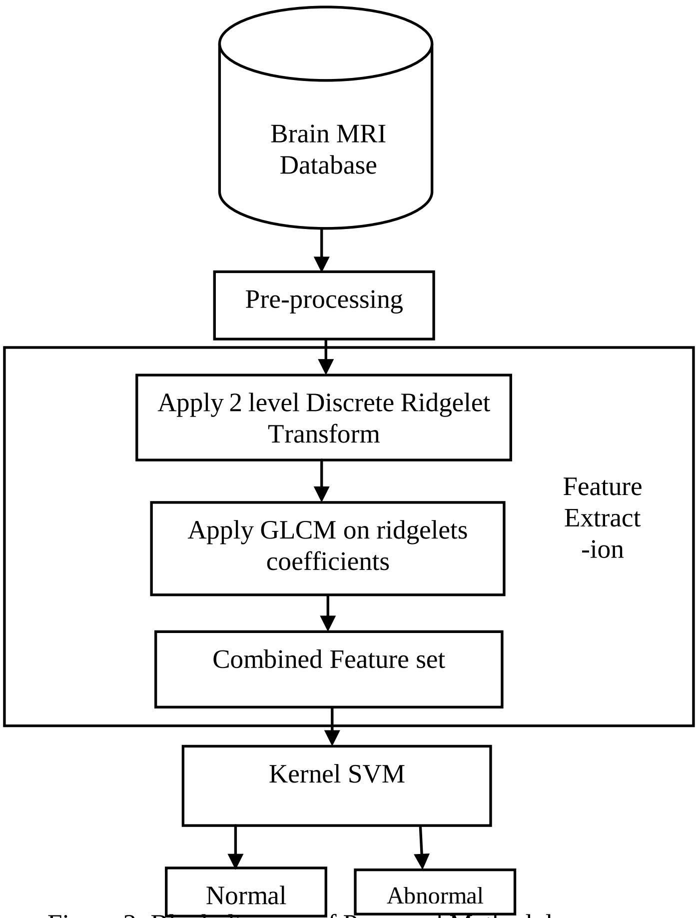


Figure 3: Block diagram of Proposed Methodology.

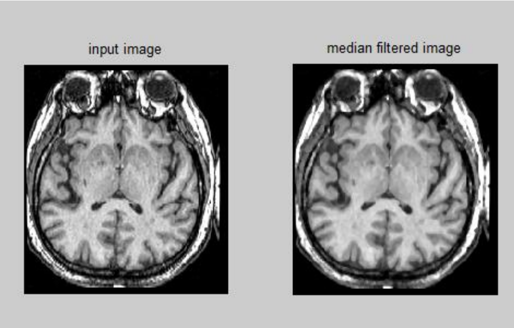


Figure5: Median filtered output.

3.Feature Extraction:

Feature extraction is done by applying DRT on input images (as algorithm1) which gives ridgelet coefficients from sub band decomposition with 2 level decomposition. The DRT is applied on MRI brain image as shown in figure6.

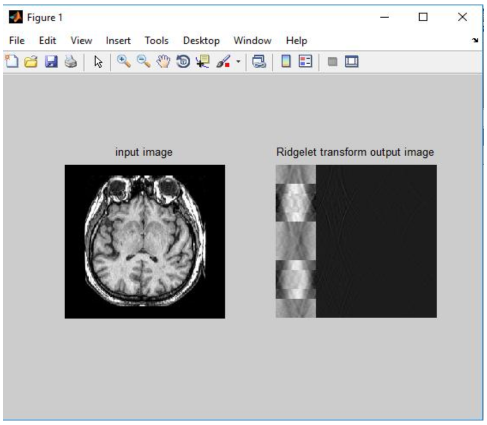


Figure 6: MRI brain image output with DRT.

After that for improving the accuracy additional features are also extracted and combined as a feature set those are statistical or con-entropy features by the Gray Level Co-occurrence Matrix(GLCM).

3.1Statistical Features:

By using GLCM extract the features for textural classification also such as Mean, Variance, Contrast, Homogeneity, Entropy, Energy, Skewness, Kurtosis, Standard Deviation and Correlation. GLCM is applied on the output of DRT calculate the all required features. Co-occurrence Matrix is used to improve the classification rate and gives details about the spatial distribution of gray scale values and it is calculated based on the distance parameter. The intensity based features are formulated as

$$Mean(m) = \frac{1}{MN} \sum_{x=1}^{M} \sum_{y=1}^{N} \left| R_i(x, y) \right| \qquad (7)$$

$$S\tan dardDeviation(\sigma) = \sqrt{\frac{1}{MN} \sum_{x=1}^{M} \sum_{y=1}^{N} (R_i(x,y) - m)^2} \qquad (8)$$

Where R_i (x, y) is the value at (x, y) of ith sub band of DRT with size MXN

M= Total number of rows. N=Total number of columns.MN= Total size of an image.

Co-occurrence matrix is based on d (x1, y1) and sample distance function d (1,1) this means one pixel right and one pixel down. The remaining features are formulated from co-occurrence C (i, j) matrix as follows

$$Contrast = \sum_i \sum_j (i-j)^2 c(i, j) \qquad (9)$$

$$Homogeneity = \sum_i \sum_j \frac{1}{1+(i-j)^2} C(i, j) \qquad (10)$$

$$Energy = \sum_i \sum_j C^2(i, j) \qquad (11)$$

$$Entopy = -\sum_i \sum_j C(i, j) * \log_2 (C(i, j)) \qquad (12)$$

The parameters variance, skewness, kurtosis are depending on the histogram of the co-occurrence matrix image. C(i) is the image histogram of co-occurrence matrix.

$$Variance(\mu) = \sum_{i=0}^{L-1} (i-m)^2 * C(i) \qquad (13)$$

$$Skewness(sk) = \sum_{i=0}^{L-1} (i-m)^3 * C(i) \qquad (14)$$

$$Kurtosis(ku) = \sum_{i=0}^{L-1} (i-m)^4 * C(i) \qquad (15)$$

L is the intensity of the image, m is the mean value, after calculating all these feature points combine as a feature set.

4.Classification:

Classification means organizing the input data into different groups based on their feature points. This classification consists of training and test phases. For achieving the higher performance kernel based SVM is used for classification. SVM is best suitable for binary classification but complexity with computational time kernel SVM resolve this problem, because it is non parametric nonlinear classifier it reduces the time of training samples without loss of precision. This kernel SVM is used in many applications like data mining, medical imaging applications and image processing applications. For the classification divide the data of 150 images into training and testing samples. then apply the kernel based SVM with different kernels such as Linear, Polynomial, Quadratic and RBF with cross validation along with holdout value and it classifies the input data as normal and abnormal images. Accuracy is calculated for all 150 images and tabulate the maximum accuracy.

$$Accuracy = \frac{Correctcases}{Totalcases} * 100 \qquad (16)$$

V. EXPERIMENTAL RESULTS & DISSCUSION

The proposed method is the comparative approach for classification of brain MRI with different feature extraction algorithms with kernel SVM. Total 150 images are taken for dividing the data into testing and training.

Preprocessing is applied on images then Discrete Ridgelet Transform (DRT) is decompose the image into sub bands and extract ridgelet coefficients and statistical features are also extracted with GLCM. These features are given as input to the kernel SVM classifier for the classification of brain images. Our proposed method is compared with KAZE+GLCM features and SURF+GLCM features with kernel SVM accuracies and as well as Naïve Bayies classifier. After execution these results are tabulated and represented with graph format.
The KAZE features such as location, scale, orientation, metric and count and along with these statistical features are also extract with GLCM and evaluate the accuracies with both kernel SVM and Naïve Bayies classifiers.
SURF (Speeded Up Robust Features) these used mainly for scale space extrema detection in linear scale spaces along with GLCM features are also extracted and given to the kernel SVM and Naïve Bayies for calculating the accuracies.
The accuracies of different feature extraction algorithms with kernel SVM as in Table I and shown in graph format as in figure 7. The accuracies of proposed and existing feature extraction algorithms with Naïve Bayies are in Table II. Computational time of proposed method is compared with existing methods for that the elapsed time is listed in Table III.

Table I. Accuracies of kernel SVM with KAZE, SURF and Proposed DRT with GLCM features.

S.NO	Feature Name	SVM with Linea-r kernel	SVM with Polynom-ia l kernel	SVM with Quadrat-i c kernel	SVM with RBF kernel
1.	SURF+GLCM	82.66%	88.66%	90.66%	89.56%
2.	KAZE+GLCM	93.33%	93.77%	94.33%	94.66%
3.	Proposed DRT+GLCM	92%	94.66%	95.46%	93.77%

Table III. Accuracies feature extraction algorithms with Naive Bayies classifier.

S.NO	Feature Name +Classifier	Accuracy
1	SURF+GLCM+Navie Bayies	76.66%
2	KAZE+GLCM+Navie Bayies	83.33%
3	Proposed DRT+GLCM+Naïve Bayies	89.65%

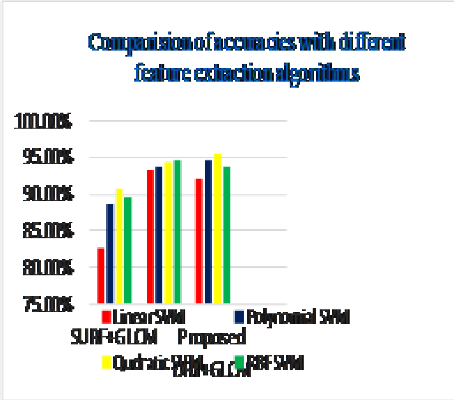


Figure 7: Accuracy comparison of proposed DRT+GLCM with KAZE +GLCM and SURF+GLCM.

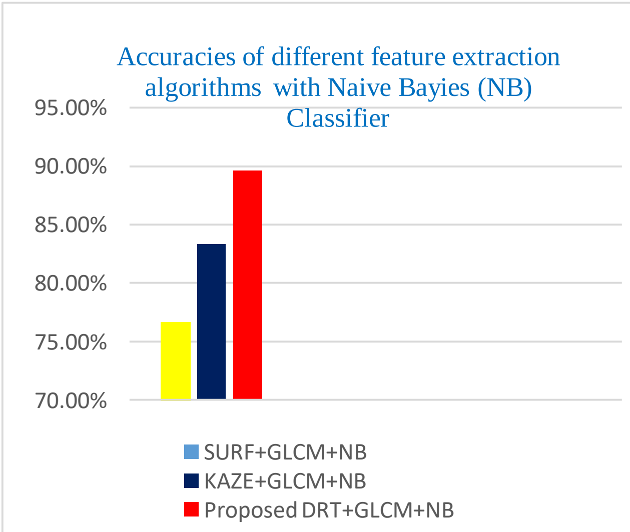


Figure 8: Accuracies of Naive Bayies with 3 Features.

Table III. Computational time for 3 different feature extraction algorithms with kernel SVM.

Feature	Computation Time
SURF+GLCM+kernel SVM	10.09sec
KAZE+GLCM+kernel SVM	63.50 sec
Proposed DRT+GLCM+kernel SVM	101.3 sec

VI. CONCLUSION AND FUTURESCOPE

In this present work, proposed an efficient method for Ridgelet based features and for textural classification statistical features are extracted with GLCM. Hybrid features(DRT+GLCM) are used for the classification of brain images and these features are fed as input to the 4 kernel SVM. Compared with the Naïve Bayies classifier our proposed method gives better accuracy of 95.42% with quadratic kernel SVM, but the computational time is little bit high compared to the existing features because the all the ridgelet coefficients are taken for the present work it takes more time so, to reduce the computational time use optimization technique for selecting the particular features.

In future, use oriented M-band ridgelet transform instead Discrete Ridgelet Transform for extracting the features with orientation also. Different classifiers can be used for increasing the classification rate along with optimization techniques and applied all these techniques on large datasets also with less computational time.

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