Journal Homepage: - www.journalijar.com

INTERNATIONAL JOURNAL OF ADVANCED RESEARCH (IJAR)

Article DOI: 10.21474/IJAR01/10963
DOI URL: http://dx.doi.org/10.21474/IJAR01/10963

RESEARCH ARTICLE

DISCRIMINATION OF PADDY VARIETIES USING WAVELET FEATURES

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Manuscript Info

Manuscript History
Received: 12 March 2020
Final Accepted: 14 April 2020
Published: May 2020

Key words:-
Energy , Multilevel 2-DWT, Neural network, and Single-level Discrete 2-DWT

Abstract

This research proposes an algorithm to implement feature extraction technique using wavelet, and use the extracted coefficients to represent the image for classification of Grains. A total of 75 Wavelet features were extracted from the high-resolution images of paddy grains. The wavelet features were employed along with ANN to identify paddy varieties. This research is aimed at comparing Single-level discrete 2-D wavelet transform and Multilevel 2-D wavelet decomposition, using ANN for discriminating Indian Paddy Varieties and also evaluate variety-wise classification of individual grains. An evaluation of the classification accuracy of wavelet features and ANN was done to classify four Paddy (Rice) grains, viz. Karjat-6(K6) and Ratnagiri-2(R2), Ratnagiri-4(R4) and Ratnagiri-24(R24). All feature models were tested for their ability to classify these cereal grains and the most suitable feature was identified from the Wavelet features for accurate classification. Single-level discrete 2-DWT gave the best classification using ANN and more accuracy can be obtained by increasing the levels of decomposition.

Introduction:-

The objective of this research was to identify and classify kernels of four paddy grain types using wavelet features. The goal was to minimize the losses incurred during harvesting, production and marketing by sowing proper type of seeds in the farm. Recently, wavelet textural features were used for classification of agricultural and food materials [1, 5, 19]. Wavelet analysis is a signal processing technique for multi-resolution image texture analysis. It is performed by decomposing the images into multiple wavelet components using a filter bank [11]. Wavelet analysis is a popular tool for categorization and classification of image texture [11, 12]. Using discrete wavelet transforms, image textures can be analysed at multiple resolutions. Therefore, the objectives of the present study were to explore the effectiveness of wavelet features for classification of cereal grain kernels, and to study the classification accuracies of feature models obtained from various combinations of wavelet features.

Wavelet transforms of the images with high frequency components truncated off seem to be able to filter out the variations such as scaling and rotation in the images. This is because low frequency components are spread in the time domain and can be treated as global property while high frequency components, concentrated in time domain, can be discarded. Information at different resolution scales provided by wavelet features lead to highly discriminating, robust classifiers. Wavelets can examine data at different scales and frequencies [17].

Textural features [6, 9] and even Color features have been used [8] by some researchers for classification purposes. The main focus of previously published research [7,10] was to determine the potential of morphological features to

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classify different grain species, classes, varieties, damaged grains, and impurities using statistical pattern recognition technique. All these features have been integrated to a single classification vector for grain kernel identification [13].

Statistical pattern classifiers, which are based on Bayes' minimum error rule [2], have so far been the tool of choice for most of the research in this field. Some of the recent research [4,14]however, has shown the potential of using ANN for classification of agricultural products. ANN have the potential to solve problems in which some inputs and the corresponding output values are known, but the relationship between the inputs and outputs is not well understood. These conditions are commonly found in grain inspection problems. Unlike most of the other industrial products, the shape, size, color and textural parameters of the agricultural produce are not governed by a unique mathematical function. This natural variability in appearance makes it a challenge for any machine vision system to recognize and classify biological entities like cereal grains[14]. A lot of research has gone into determining the potential of different features to classify different grain species, varieties, and damaged grains using statistical pattern recognition techniques.

The success of any classification process, to a large extent, depends on the classification criterion chosen for the task. A classification criterion classifies objects into two or more groups, called classes, on the basis of the quantitative features extracted from the objects. ANN classifiers are emerging as the best suited classifiers for pattern recognition which are regarded as an extension of many classification techniques.

Various NN architectures have been developed by researchers in the past decade. With the growing popularity of NN techniques in image analysis, it is important to explore the applicability of various NN architectures for classification of agricultural products including cereal grains. Presently, the identification and grading of cereal grains is done manually in India. This task is subjective and time consuming. To replace this manual assessment of grain samples a machine vision system is highly desired by the grain industry. Despite the research work, several bottlenecks have restricted the implementation of machine vision technology in grain industry. A part of the problem is slow classification process. Neural networks, which perform faster classification as compared to most of their statistical counterparts, might provide a solution to the problem of slow classification in such systems [14].

Objective:-

In light of the above problems, the objectives of this study were:

1. To extract a total of 75 wavelet features.
2. To evaluate the classification accuracy of Wavelet feature set and ANN.
3. To evaluate Variety-wise classification of individual grains using ANN.
4. To compare the performance of the Wavelet feature set for classification of Karjat-6(K6), Karjat-2(K2), Ratnagiri-4(R4) and Ratnagiri-24(R24) paddy types.
5. To find the most suitable feature from the Wavelet features for accurate classification.

Materials and Methods:-

Material and Grain samples:

Sony Make 18.9 Megapixels Digital camera, Black cloth Sheet for background, Photographs of the Paddy seeds, Reference object. The Seed Testing Laboratory-pune, India, provided the grain samples used in this study. The unclean commercial samples of four paddy grains, Karjat-6(K6), Karjat-2(K2), Ratnagiri-4(R4) and Ratnagiri-24(R24) were collected.

Image acquisition system:

The images were acquired using a Sony Make 18.9 Megapixels Digital camera from different distances. Randomly any numbers of seeds were placed on the black background with the kernels not touching each other. The camera was held in such a manner that it was horizontal to the plane. The light source was not defined as such, the seeds were exposed to direct sunlight and the images were taken from variable illumination.

Algorithm development:

The image analysis software was developed in Matlab version 7.12.0.635 (R2011a) under the Windows environment. In order to extract object features, image segmentation and any necessary morphological filtering was done. A clearly defined object was labeled and processed independently. After all the binary objects in the image are labeled, each object was treated as a binary image. A total of 75 Wavelet features were extracted by the algorithm and then used in different combinations for evaluating the performance and the obtained statistics were fed to ANN classifier.

Wavelet analysis:

The limitation of Fourier techniques is that each Fourier coefficient contains complete information about the behavior of the series at one frequency but no information about its behavior at other frequencies. The deficiencies of Fourier techniques have led researchers to develop various multiresolution representations of functions. The basic idea behind this technique is to represent functions with a collection of coefficients each of which provides some limited information about both the position and the frequency of the function. Wavelet is one such multiresolution function. It consists of a coarse overall approximation together with detail coefficients, which influence the function at various scales.

Wavelet analysis is a signal analysis tool for characterization of image texture at multiple resolutions. Wavelet analysis is the breaking up of a signal into shifted and scaled versions of the original (or mother) wavelet. The continuous wavelet transform (CWT) of a signal x(n) results in a set of wavelet coefficients as follows

$$W(t,s) = \frac{1}{\sqrt{s}}\int_{-\infty}^{\infty} x(n)\, \psi_{t,s}(n)dn \qquad (1)$$

Where W(t,s) is the CWT coefficients of a time signal, x(n), t is the translation parameter, measure of location, and s the scale parameter, inversely related to frequency;

$$\psi_{t,s}(n)dn = \psi((n-1)/s) \qquad (2)$$

which is the mother wavelet ψ translated by t and scaled by s. W(t,s) can be interpreted as the cross-correlation between the signal and the mother wavelet translated by ‘t’ and scaled by ‘s’[3].

Although the CWT can be implemented in discrete format, there is too much redundant information in the decomposed signals. Therefore, the discrete wavelet transform is used with down-sampling at each level of decomposition to remove the redundant information [18]. Discrete wavelet transforms (DWT) of images are implemented using digital filters and downsamplers.

The one-dimensional DWT provides two sets of coefficients at each level of decomposition; namely, approximation and details. Similarly, two-dimensional DWT of image leads to a decomposition of approximation coefficients at level j in four components: the approximation at level j + 1, and the details in three orientations (horizontal, vertical, and diagonal) thus giving 4 sets of coefficients at each level of decomposition [3].

Rows of the input image are first passed through the low- pass filters, h(n) and high-pass filters, g(n) followed by down-sampling along the rows by a factor of 2[11]. The columns of resulting images from both filters are sent through low- and high-pass filters followed by down-sampling along the columns to obtain four sets of coefficients; namely, approximation (A), horizontal (H), vertical (V), and diagonal (D) details [3]. As the levels of decomposition increase, the amount of down-sampling increases, resulting in lower resolutions at successive levels. At the first level of decomposition, high-frequency components are extracted with a higher spatial resolution. At higher levels of decomposition, successively lower-frequency components are extracted at lower resolutions [15].

Among the many mother wavelet functions, the Daubechies wavelet was used in this study as they have the ability to provide highest number of vanishing moments for a given support width. The fourth order Daubechies wavelet has a vanishing moment of 4. Therefore, it can decompose the polynomial of order 3 to produce null details. It means that this wavelet function can analyse signals with trends of a third order polynomial [16].

Determination of Wavelet features:

The images of each kernel were subjected to Single-level discrete 2-D wavelet decomposition at level 4 with respect to first-order Daubechies wavelet (db1). The approximation coefficients, details coefficients matrices (horizontal, vertical, and diagonal), were obtained by wavelet decomposition at level 4. Mean, standard-deviation and variance for all the four coefficients of each color band (R, G, and B) were calculated.12 wavelet features for each color band were extracted giving total of 36 features for each kernel.

Multilevel 2-D wavelet decomposition at level 3 using a forth-order Daubechies wavelet(db4) was also applied. Energy for 2-D wavelet decomposition was obtained for horizontal, vertical and diagonal orientations. Percentage of energy corresponding to the approximation, and the percentages of energy corresponding to the horizontal, vertical, and diagonal details; and the sum of percentages of energy of horizontal, vertical, and diagonal details were calculated for each color band(R, G, and B). 13 wavelet features for each color band were extracted giving total of 39 features for each kernel. Thus bringing the total number of wavelet features to 75 for each kernel.

Neural network architectures:

Neural networks are massively parallel connecting systems consisting of an extremely large number of simple processors with many interconnections between the elements. They are based on the concept of biological nervous system. NNs explore many hypotheses simultaneously using massive parallelism instead of sequentially performing a programme of instructions. Neural networks have the potential for solving problems in which some inputs and corresponding output values are known, but the relationship between the inputs and outputs is not well understood or is difficult to translate into a mathematical function. Thus, these classifiers have a great potential in tasks involving grading, sorting and identifying agricultural products.

Neural networks have proven themselves as proficient classifiers and are particularly well suited for addressing non-linear problems. The seventy-five wavelet features and their different combinations were used as inputs to a neural network and the type of the seed as target. Given an input, which constitutes the wavelet features of a seed, the neural network is expected to identify the type of the seed which is achieved by neural network training. Data for classification problems were set up for a neural network by organizing the data into two matrices, the input matrix and the target matrix. Each column of the input matrix had wavelet features assigned to it. Each corresponding column of the target matrix had two to four elements.

Two-layer backpropagation supervised neural networks with a single hidden layer of 20 neurons were used to train the network. For this study backpropagation algorithm supervised algorithm was used. Back-propagation networks are the most commonly used networks because of their ability to generalize. The number of nodes as 20 was used to train the network. The trained neural network was tested with the testing samples to find how well the network will do when applied to data from the real world. To measure how well the neural network has fit the data the confusion matrix was plotted across all samples and the data presented is from confusion matrix.

Artificial neural network configuration:

Number of hidden layer=1, Number of neurons =20, Error function= Mean Squared Error, Validation check stops, Transfer function: Hyperbolic tangent sigmoid

Training and test data for ANN:

To evaluate the classification accuracy of wavelet feature set and neural network, color images of 3938 kernels for K6, 5103 for K2, 3201 for R4 and 1604 kernels for R24 were taken. For each kernel from all the sets, 75 wavelet features were extracted and used as input to the neural networks. From the each set 60% kernels were used for training and 40% kernels for testing of each grain.

To study the effect of various parameters on the classification ability of the ANN, First 36 parameters concerning Mean, standard-deviation and variance for all the four coefficients of each color band (R, G, and B) for single-level-2DWT were used for classifying the grains in four categories. Then, same 36 parameters for single-level-2DWT-level4 were used for classifying the grains. Similarly 39 parameters concerning 13 wavelet features for each color band for Multilevel-2DWT-level3 as explained in section 3 were used and analysis was also done using all 75 parameters concerning 36 plus 39 parameters for 1-level-2DWT-level4&Multilevel-2DWT-level3 for classifying the grains in four categories.

These feature sets are referred as single-level-2DWT(1L) ,single-level-2DWT-level4(1L-L4), Multilevel-2DWT-level3(MLL3) and 1-level-2DWT-level4&Multilevel-2DWT-level3(1L4&ML3) . Pattern classification was done using a two-layer BPN with LM training functions and the results of the same were compared for different feature sets. The choice of the BPN classifier was based on previous research conducted by [13].

Mathematical model:

Let S be system that classifies seeds form the four varieties S= {…..}

Identify I/P as I_i

S= {I_i,….}
I_i= {i_1, i_2 | $i_1 \in$ image dataset and $i_2 \in$ any one of the four wavelet feature models}
Where,
i_2 = { single-level-2DWT(1L) ^ single-level-2DWT-level4(1L-L4) ^ Multilevel-2DWT-level3(MLL3) ^ 1-level-2DWT-level4&Multilevel-2DWT-level3(1L4&ML3)}

The whole Wavelet feature set obtained is as follows:

Wavelet feature set= {μ_{AR1}, μ_{AG1}, μ_{AB1}, σ_{AR1}, σ_{AG1}, σ_{AB1}, var_{AR1} , var_{AG1} , var_{AB1} ,μ_{HR1}, μ_{HG1}, μ_{HB1}, σ_{HR1}, σ_{HG1}, σ_{HB1}, var_{HR1} , var_{HG1} , var_{HB1} ,μ_{VR1}, μ_{VG1}, μ_{VB1}, σ_{VR1}, σ_{VG1}, σ_{VB1}, var_{VR1} , var_{VG1} , var_{VB1} , μ_{DR1}, μ_{DG1}, μ_{DB1}, σ_{DR1}, σ_{DG1}, σ_{DB1}, var_{DR1} , var_{DG1} , var_{DB1} , μ_{AR4}, μ_{AG4}, μ_{AB4}, σ_{AR4}, σ_{AG4}, σ_{AB4}, var_{AR4} , var_{AG4} , var_{AB4} ,μ_{HR4}, μ_{HG4}, μ_{HB4}, σ_{HR4}, σ_{HG4}, σ_{HB4}, var_{HR4} , var_{HG4} , var_{HB4} ,μ_{VR4}, μ_{VG4}, μ_{VB4}, σ_{VR4}, σ_{VG4}, σ_{VB4}, var_{VR4}, var_{VG4} , var_{VB4} , μ_{DR4}, μ_{DG4}, μ_{DB4}, σ_{DR4}, σ_{DG4}, σ_{DB4}, var_{DR4} , var_{DG4} , var_{DB4} , E_{AR}, E_{HR1}, E_{HR2}, E_{HR3}, E_{VR1}, E_{VR2}, E_{VR3}, E_{DR1}, E_{DR2}, E_{DR3}, $EDetail_{R1}$, $EDetail_{R2}$, $EDetail_{R3}$, E_{AG}, E_{HG1}, E_{HG2}, E_{HG3}, E_{VG1}, E_{VG2}, E_{VG3}, E_{DG1}, E_{DG2}, E_{DG3}, $EDetail_{G1}$, $EDetail_{G2}$, $EDetail_{G3}$, E_{AB}, E_{HB1}, E_{HB2}, E_{HB3}, E_{VB1}, E_{VB2}, E_{VB3}, E_{DB1}, E_{DB2}, E_{DB3}, $EDetail_{B1}$, $EDetail_{B2}$, $EDetail_{B3}$ }

Four feature set models were derived from above set as follows

First feature set:

1L $\subseteq$ Wavelet feature set

1L = { μ_{AR1}, μ_{AG1}, μ_{AB1}, σ_{AR1}, σ_{AG1}, σ_{AB1}, var_{AR1} , var_{AG1} , var_{AB1} ,μ_{HR1}, μ_{HG1}, μ_{HB1}, σ_{HR1}, σ_{HG1}, σ_{HB1}, var_{HR1} , var_{HG1} , var_{HB1} ,μ_{VR1}, μ_{VG1}, μ_{VB1}, σ_{VR1}, σ_{VG1}, σ_{VB1}, var_{VR1} , var_{VG1} , var_{VB1} , μ_{DR1}, μ_{DG1}, μ_{DB1}, σ_{DR1}, σ_{DG1}, σ_{DB1}, var_{DR1} , var_{DG1} , var_{DB1} , }

Second feature set:

1L-L4 $\subseteq$ Wavelet feature set

1L-L4 = {μ_{AR4}, μ_{AG4}, μ_{AB4}, σ_{AR4}, σ_{AG4}, σ_{AB4}, var_{AR4} , var_{AG4} , var_{AB4} ,μ_{HR4}, μ_{HG4}, μ_{HB4}, σ_{HR4}, σ_{HG4}, σ_{HB4}, var_{HR4} , var_{HG4} , var_{HB4} ,μ_{VR4}, μ_{VG4}, μ_{VB4}, σ_{VR4}, σ_{VG4}, σ_{VB4}, var_{VR4}, var_{VG4} , var_{VB4} , μ_{DR4}, μ_{DG4}, μ_{DB4}, σ_{DR4}, σ_{DG4}, σ_{DB4}, var_{DR4} , var_{DG4} , var_{DB4} , }

Third feature set:

ML-L3 $\subseteq$ Wavelet feature set

ML-L3 = { E_{AR}, E_{HR1}, E_{HR2}, E_{HR3}, E_{VR1}, E_{VR2}, E_{VR3}, E_{DR1}, E_{DR2}, E_{DR3}, $EDetail_{R1}$, $EDetail_{R2}$, $EDetail_{R3}$, E_{AG}, E_{HG1}, E_{HG2}, E_{HG3}, E_{VG1}, E_{VG2}, E_{VG3}, E_{DG1}, E_{DG2}, E_{DG3}, $EDetail_{G1}$, $EDetail_{G2}$, $EDetail_{G3}$, E_{AB}, E_{HB1}, E_{HB2}, E_{HB3}, E_{VB1}, E_{VB2}, E_{VB3}, E_{DB1}, E_{DB2}, E_{DB3}, $EDetail_{B1}$, $EDetail_{B2}$, $EDetail_{B3}$ }

Fourth feature set:

1L4&ML3 $\subseteq$ Wavelet feature set

1L4&ML3 = {μ_{AR4}, μ_{AG4}, μ_{AB4}, σ_{AR4}, σ_{AG4}, σ_{AB4}, var_{AR4} , var_{AG4} , var_{AB4} ,μ_{HR4}, μ_{HG4}, μ_{HB4}, σ_{HR4}, σ_{HG4}, σ_{HB4}, var_{HR4} , var_{HG4} , var_{HB4} ,μ_{VR4}, μ_{VG4}, μ_{VB4}, σ_{VR4}, σ_{VG4}, σ_{VB4}, var_{VR4}, var_{VG4} , var_{VB4} , μ_{DR4}, μ_{DG4}, μ_{DB4}, σ_{DR4}, σ_{DG4}, σ_{DB4}, var_{DR4} , var_{DG4} , var_{DB4} , E_{AR}, E_{HR1}, E_{HR2}, E_{HR3}, E_{VR1}, E_{VR2}, E_{VR3}, E_{DR1}, E_{DR2}, E_{DR3}, $EDetail_{R1}$, $EDetail_{R2}$, $EDetail_{R3}$, E_{AG}, E_{HG1}, E_{HG2}, E_{HG3}, E_{VG1}, E_{VG2}, E_{VG3}, E_{DG1}, E_{DG2}, E_{DG3}, $EDetail_{G1}$, $EDetail_{G2}$, $EDetail_{G3}$, E_{AB}, E_{HB1}, E_{HB2}, E_{HB3}, E_{VB1}, E_{VB2}, E_{VB3}, E_{DB1}, E_{DB2}, E_{DB3}, $EDetail_{B1}$, $EDetail_{B2}$, $EDetail_{B3}$ }

Identify O/P as O
S= {I_i, O,….}
O= {T | T is type of seed from the four types to be classified}

Identify Process as P
S= {Ii, O, P, ….}
P= {classify ( ) | classify( ) perform match of seed with the features from feature vector}

Identify failure cases as F
S= {Ii, O, P, F….}
Failure occurs when,

i. The images are taken in variable illumination
ii. The different seeds have same features

Identify success cases as G
S= {Ii, O, P, F ,G}
Success is defined as for given set of images system gives output with exact match.

Results and Discussions:-

Variety-wise classification of individual grains using ANN:

The effects of various wavelet parameters on the accuracy of the variety-wise classification were studied using the selected ANN configuration described above. Combinations of the wavelet parameters (Four feature set) as mentioned in the training and test data for ANN were used. As mentioned earlier, four pairs of training/test data (1. K6, K2; 2. R24, R4; 3. K6, K2, R24; 4. K6, K2,R4, R24) were prepared for this study. The total numbers of seeds for different variety are Table 1 presents the representative results of testing of ANNs with features.

Following table shows the gross results of classification accuracy, i.e. total number of correct classification out of test data sets—with variety-wise break-up.

Table 1:- Variety-wise classification of individual grains.

Seeds	**1L**	**1L-L4**	**ML-L3**	**1L4&ML3**
Variety 1				
K6	71.7	82.4	54.5	**84.4**
K2	**90.8**	84	80.9	87.5
Variety 2				
R24	95.6	93.2	73.9	**97.3**
R4	94.3	**94.4**	83.2	92.1
Variety 3				
K6	21.7	**41**	36.4	36.4
K2	**95.1**	87.5	77.9	81.5
R24	95.3	**95.6**	77.1	95.2
Variety 4				
K6	20.3	**52.8**	27.4	35
K2	**88.3**	87.3	74.9	76
R4	**91**	87.3	57.3	79
R24	85.7	**86.1**	76.6	75.9

The results showed that the accuracy of classification of the ANN was best most of the time when single-level-2DWT-level4(1L-L4) parameters were used in training and testing of the ANN and decreased for Multilevel-2DWT-level3(ML3) parameters. In case of K6 the classification accuracies of was found to be low which can be attributed to the fact that few images were taken in less illumination to test the effect of illumination. The classification accuracy may improve when shape, color and texture will be included in the feature set.

Effect of using different wavelet parameters on the accuracy of classification:

Table 2 gives the Total accuracy for different feature set and different variety of grains. The classification accuracies based on 1L,1L-L4,ML-L3 AND 1L4&ML3 features using a BPN classifier are shown.

Table 2:- Total accuracy% for different feature sets and different variety of grains.

Total Accuracy %					
Sr.no.	**Variety of Seeds**	**1L**	**1L-L4**	**ML-L3**	**1L4&ML3**
1.	**K6 , K2**	83.16	83.35	70.20	**86.20**
2.	**R24,R4:**	**94.83**	93.97	79.61	94.07
3.	**K6,K2,R24:**	69.98	**72.68**	63.40	67.80
4.	**K6,K2,R4,R24:**	69.09	**76.85**	59.80	65.6

Average Accuracy%	79.27	**81.71**	68.25	78.41

Table 2 and Fig 1 show the overall classification accuracy for different varieties of seeds. To be specific for first group of seeds accuracy shown is 86.2% for 1L4&ML3 features, for second group of seeds 94.83% for 1L features, for third group of seeds 72.68% for 1L-L4 features, for fourth group of seeds 76.85% for 1L-L4 features is shown. Fig 1 proves that ML3-feature set was inferior and 1L-L4 features set was found to be superior followed by 1L features.

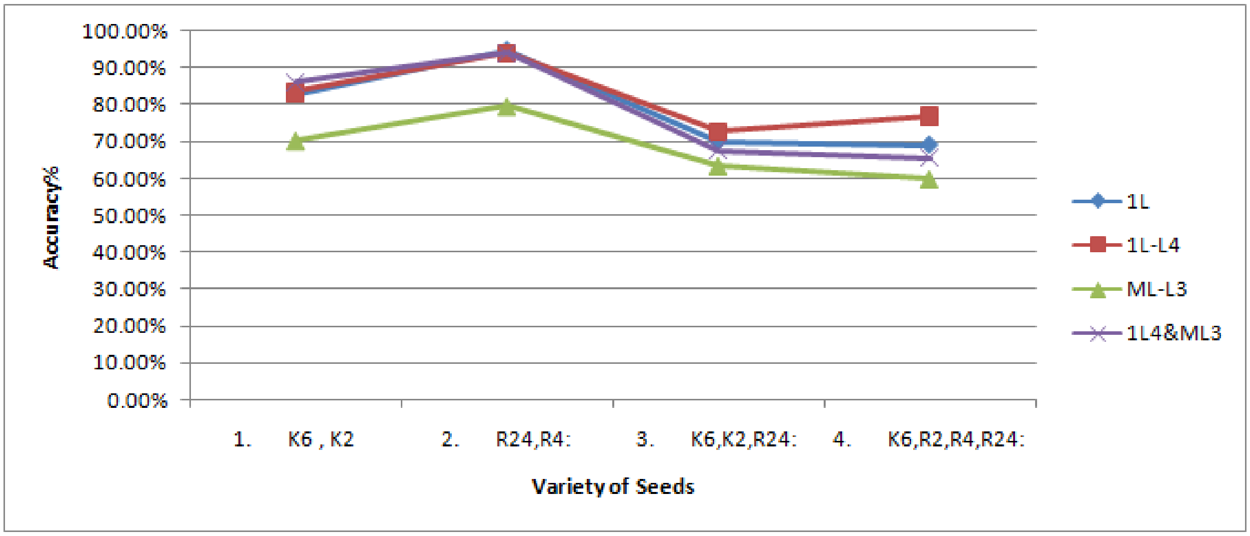

Fig 1:- Total accuracy% for different feature sets and different variety of grains.

Conclusions:-

In addition to the Single-level discrete 2-D wavelet transform, Multilevel 2-D wavelet decomposition was also done to extract features from images of individual grains. The different feature sets in combination were formed and the same were assessed for classification of grains. The presented method for the varietal identification of paddy shows around 69% to 94.8% accuracy. The average accuracy shown is 81.71% for 1L-L4 features. The time required to perform the analysis is very short. The most satisfactory results were delivered by the measurement of 1L-L4 parameters. ML-L3-Feature set gave lower accuracy than all other sets. Thus it can be concluded that Single-level discrete 2-DWT have a significant role in discriminating the paddy varieties than the energy features calculated from Multilevel 2-D wavelet decomposition. Thus Single-level discrete 2-DWT have the potential to improve the classification accuracy of the machine vision systems used for classification of paddy grains, more accuracy can be obtained by increasing the levels of decomposition as at higher levels of decomposition, successively lower-frequency components are extracted at lower resolutions.

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