

## RESEARCH ARTICLE

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# Performance Analysis of Cereals Grains using Neural Network & Multi Support Vector Machine

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## Abstract

**Objectives:** To classify cereal grain using a multi-support vector machine and artificial neural network for better accuracy. To build a system for cereals grains classification with the use of image processing techniques. **Methods:** Using a CCD camera, the method starts with image acquisition. To acquire images Grayscale conversion, noise reduction, binarization, edge detection, and morphological operations are applied. Using the edge detection technique edge of the objects is predictable. The watershed algorithm is used for the segmentation of touching and overlapping cereals kernels. Local Binary Pattern (LBP) texture feature and color features extracted from segmented images. For image classification, the features extraction method is used. **Findings:** We have incorporated various parameters like shape, size, length, width, major axis length, and minor axis lengths on different cereals like rice, barley, millet, sorghum, wheat, and millet. There are a total of 96 images of the data set are used to train or test the model. Out of that 70% are training and 30% are testing. **Improvements:** In the proposed MSVM technique, we have achieved 89.7% accuracy and in the ANN technique the accuracy is 92.3% which is higher than the conventional SVM technique. **Novelty:** The proposed technique is based on the Multi Support Vector Machine (MSVM) and Artificial Neural Network (ANN). We have compared the MSVM and ANN with the SVM technique.

**Keywords:** Segmentation; SVM; Cereals Quality; Watershed Algorithm; Local Binary Pattern; Classification of grain; neural network

## 1 Introduction

Cereal is a seed that belongs to the Poaceae family. There are different types of cereals like rice, barley, millet, sorghum, wheat, millet, etc. Cereals are produced in many areas of the world. India is the second largest country for the production of cereal in the entire world. Cereals' commercial value and genetic characteristics depend on different types of its varieties. Cereal grains are decided by the grade and price factor.

Cereal seeds are identified using the classification of different types of cereals. Manual classification methods are being used largely by local industry to differentiate cereals grain by local geometric parameters. This paper proposed a method that processes the

digital image of cereals grains and extracts the relevant features. Morphological features of cereals grains are used to check the types of rice. Image processing techniques are applied to extract various types of cereal grains and classified the cereal grain based on several features. The collected features help full neural network pattern recognition and support vector machine for categorizing granules of cereal.<sup>(1)</sup>

Cereal is the most important food crop that all human consumes in every world, particularly in Asia. It is primarily categorized according to its grain shape. The hull cereal has been harvested from the plant. The hull is burned for use as an energy source since it is not eaten by humans. When the hull is distant from cereal it has been predictable as brown cereal. The bran and germs give the brown cereal. Its color can vary from light yellow to red to dark purplish black<sup>(2)</sup>.

The cereal contains larger amounts of dietary fiber; vitamins, minerals, and other health-related components than the white center portion of the kernel (endosperm). That outer portion of the kernel also contain more lipid (fats) material, making brown cereal more predisposed becomes rancid. So it has a shorter shelf life compared to milled white cereal.

To get good quality cereal, first, the cereal must be filtered during an assured system before machine vision can do its job. Cereal quality examination using naked eyes is unproductive; thus for the identification of cereal, there are many systems and technologies available. The cereal can be classified by many features of the cereal such as the physical shape, length, width, color, amount of foreign matter, amount of nitrogen<sup>(3)</sup>, moisture content, internal broken, and many more<sup>(4)</sup>. Features can be detected using the technologies like computer image analyses, remote-sensing technology, image processing techniques, machine vision, neural network, and digital imaging. By applying the algorithm it will display how machine vision is capable to sort the cereal using effective routine calculation and using image filters techniques results are obtained<sup>(5)</sup>.

The previous study is based on ANN and SVM. It defines only a single classification of cereal. SVM is used for single cereal grains classification and has limited features. SVM has only two classes. Due to this limitation, the accuracy of SVM is degraded compared to the proposed MSVM technique. The current scenario is multigrain classification. To overcome the performance of SVM, we have proposed the MSVM technique for multigrain classification. In the MSVM technique, we have incorporated more features. MSVM is a better technique for multi-class grain classification. We have also compared the results of MSVM, and ANN with the SVM technique.

## 2 Methodology

The methodology is used to segment and classify the objects. For the classification task, six-grain varieties were sampled: rice, barley, millet, sorghum, wheat, and milled. Figure 1 shows the block diagram of the proposed system model.

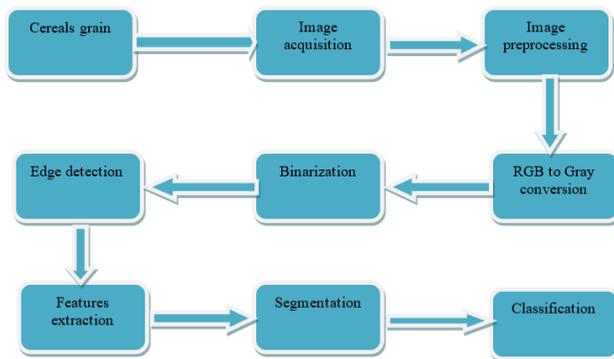


Fig 1. System model of proposed work

### 2.1 Image Acquisition

Image acquisition is the first process. The first database is rice. The second contains barely cereal. The third dataset is millet cereal. The fourth dataset is sorghum cereal. The fifth dataset is wheat cereal. The sixth database is milled cereal. Image acquisition is done by taking pictures of different cereal images with an internal web camera. Every database contains 8 images of each class which is a total of 48 images of ISL numbers that have a simple and consecutive class of images. Figure 2a shows the photographs of cereals sample taken using a Huawei GR5 CCD Camera. Figure 2b shows the gray scaled image. To achieve good performance Controlled environment is used. When taking images keep the distance between the cereals sample and camera consistent.

A homogeneous lighting scheme is also used. However, there is a still problem with non-uniform lighting, which produces segmentation faults<sup>(6)</sup>. To reduce the non-uniform illumination effect an Image of cereals sample and background is used. The acquired images have resolutions of 3966 x 2976 pixels.

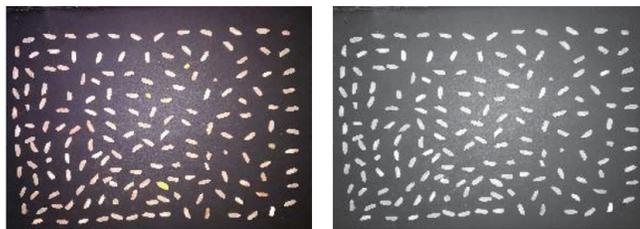


Fig 2. a) Input image of cereal sample; b) Gray Scaled Image

### 2.1.1 Preprocessing

Converting RGB color images to gray scale image at the first stage. The goal of this stage is to simplify the image, and reduces the code's complexity. Figure 2b shows the Gray scaled images.

The difference between of two images is then calculated by subtracting the background image from the foreground image. The aim of this step is to eliminate the effects of uneven lightings and light spots. To acquire images, the uniform lighting conditions are considered. However, due to the small size of wheat kernels, a slight changing in lighting affects to the segmentation process. As a result, luminous spots on an image are removed by subtracting the background image from foreground image.

### 2.1.2 Thresholding

Thresholding is one of the binarization techniques. This technique is used to convert an image to binary form in 0's and 1's. In Otsu Binarization, the threshold value is used for the bimodal image that can be automatically calculated from the image histogram<sup>(7)</sup>. That's why Otsu's binarization is used for this approach. The binaries image is shown in Figure 3a.



Fig 3. a) Binarized Image; b) Contour Detection Image

### 2.1.3 Smoothing

Smoothing is used to reduce noise and prepare the image for further processing. To remove noise, a Gaussian blur filter is used. It is the low pass filter (LPF) that can solve the problem of blurring the image and removing noise. To get the proper image, blurring is removed by the low pass filter technique with convolving kernel. It also helps to remove noise. Gaussian filter is used to reduce high-frequency contents like sharp edges.

### 2.1.4 Morphological operations

To eliminate small white noises of the binarized image, the morphological operation of erosion followed by dilation is utilized. Morphological opening ensures the background and foreground regions by the distance between the center of the object and the region. Morphological closing is the reverse of opening. It helps to close small gaps and small points inside the visual area.

## 2.2 Segmentation

After preprocessing segmentation of objects is done. After using the contours, extract the separate objects from the input RGB image. Cereals seeds, paddy seeds, and foreign objects of RGB images are separated using the outputs of these modules.

The contour is a curve, a combination of the same color or same intensity point constantly drawn along the boundary. In object detection, object recognition and shape analysis contours are utilized. The contour detection image is shown in Figure 3 b.

Using the watershed algorithm, touching and overlapped objects can recognize. Due to the noise and non-uniform illumination watershed algorithm gives over the segmented image<sup>(8)</sup>. Therefore, the marker-based watershed algorithm is used in this method. It specifies whether all points are to be merged or not.

### 2.3 Feature Extraction

In feature extraction, an image is defined as extracting the color and texture. In the model, extracted features are defined. Features are extracted from new image samples using linear kernel-based SVM techniques. Extracted features are used in the identification and classification process. Objects are classified as cereals, paddy, weed seeds, and stones. The block diagram illustrates the procedure for the identification and classification of image samples as shown in Figure 4.

The feature vector implies an abstraction of an image. Normally real, integer or binary values are produced. To represent an image a feature vector is used. For better classification accuracy, it is necessary to select the most proper feature extraction method. For training and testing the dataset proposed algorithm is used to extract nine color features and an LBP texture feature.

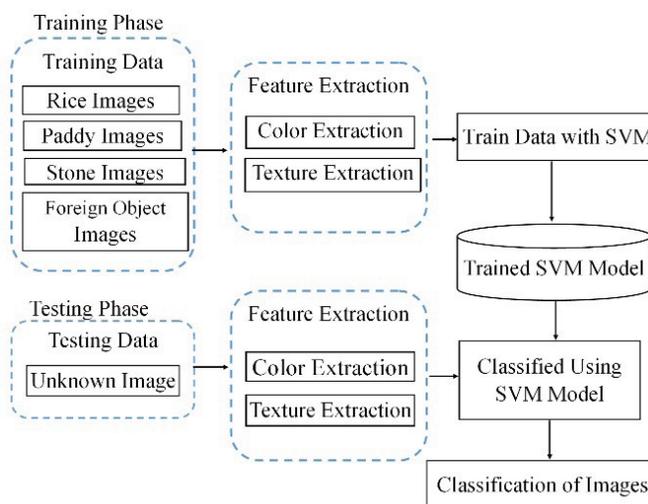


Fig 4. Classification using SVM Model

LBP gives support to a description of a digital image texture. The first step is separating the image which needs to extract the features into multiple regions. The features are in the binary form that defines the neighboring pixels of the regions. In only one histogram the obtained features are concatenated. The entire image is represented as a histogram standing.

#### 2.3.1 Texture Extraction

The image samples are having different textures. They provide properties about the intensity variation of a surface. They estimate the properties such as reliability and efficiency.

Texture features of the segmented images are extracted using a local binary pattern (LBP). Local Binary Pattern is a very proficient and simple quality descriptor. It labels the pixels of an image by comparing them with its neighboring pixels. It labels the pixels of an image. The feature numbers are given as a binary numbers.

Simplicity and discriminative are the main property of LBP that's why it is becoming a popular texture descriptor in various applications. For texture analysis, LBP is a unifying approach to the traditional, divergent, statistical, and structural models<sup>(9)</sup>. LBP descriptor in the real world has the most important properties. For gray-scale changes like illumination variations, LBP robustness to monotonic. Due to computational simplicity, LBP helps to analyze images with the challenge of real-time settings. The main feature of the LBP descriptor is that it captures the fine-grained information of the image.

## 2.4 Multi-Class Support Vector Machine

Multi-class support vector machine technology is used to classify sample objects into cereals, paddy, foreign objects, and stone categories. A support vector machine is a supervised learning model<sup>(10)</sup>. It is connected with learning algorithms that support the evaluation of data in classification and regression analysis.

The MSVM technique is used to implement an optimal hyper plane that helps to categorize into linear separable patterns. MSVM is mainly set to maximize the margin, which will verify that the input pattern will be classified correctly.

MSVM is capable of statistical learning. To identify and classify the patterns multi-class support vector machine is used<sup>(11)</sup>. Using MSVM the linear patterns are easily discernible and separated in lower dimensions.

## 3 Results and Discussion

In the cereals seeds segmentation module, input images are segmented into objects and categorized into four categories as cereals, paddy, stone, and foreign objects. To improve the performance of cereals segmentation preprocessing is required. To execute this requirement, preprocessing stage includes noise removal, subtraction, binarization, and morphological operations. In the estimation of the solution, execution time plays a major role. Time taken for preprocessing is mentioned in Table 1. In Table 2, evaluation results of different types of cereals are discussed. Comparative analysis of the results is discussed in Table 4 and Figure 6.

In this paper, we have compared the proposed multi-support vector machine (MSVM) and artificial neural network technique with the existing support vector machine technique. We have represented the mathematical formula of SVM and MSVM in equation no. (4) and (5).

### 3.1 Classification of Result using Precision and Recall Rate

**Table 1.** Time taken for Preprocessing

Image Size (Pixels)	Elapsed Time(s)
2976 x 3968	0.843
4160 x 3120	0.867
4608 x 3456	0.937

Using two specific performance measures the used method is evaluated. Those are precision and recall rate. Precision is also known as positive predictive value and recall is sensitivity. Precision is the fraction to truly identified instances throughout all selected instances. A recall is used to correctly identify instances that have been selected over the whole relevant instances. For understanding and measure of significance, both measurements are building. The F-measure also called harmonic mean is used to combine precision and recall.

$$Precision(\rho) = \frac{Tp}{(Tp+FP)} \dots\dots\dots (1)$$

If the precision value is 0.0 then there is no precision and 1.0 for full or perfect precision.

$$Recall (R) = \frac{Tp}{(Tp+Fn)} \dots\dots\dots (2)$$

If the recall value is 0.0 then there is no recall and 1.0 for full or perfect recall.

$$F\ measure = 2 * \frac{(P*R)}{(P+R)} \dots\dots\dots (3)$$

This is the harmonic mean of the two fractions. This is sometimes called the F-Score or the F1-Score and might be the most common metric used on imbalanced classification problems.

In this solution, cereals segmentation plays a major role. Segmentation accuracy is more important because its output is the cereals classification module where cereals, paddy, foreign objects, and stone identification are done. Different cereals categories, foreign objects, paddy, and stone of image are evaluated for accuracy of the segmentation module. For the segmentation method, pprecision and recall rate are calculated. Tp is the correctly segmented objects of the cereals sample image. Fp is the values measures for wrongly detectedunnecessary objects. Fn is the undetected object of the cereals sample. The segmentation process has a 93.75% average precision rate and a 99.40% recall rate. The F Measure value of segmentation is 96.28%.

In the sample image, the precision and recall rate is measured. But some cereals kernels in the image are not recognized as objects. There is a low color difference between the background and the cereals kernel. This problem generates when difficult to segment the image of the red cereals sample as shown in Figure 5a.

The image acquisition process used the regular light condition. We can decrease the impact of non-uniform light circulation by using background and foreground images. But in the non-uniform light distribution condition, it affects the segmentation

result badly as shown in Figure 5b.

In the system model, feature extraction and classification are the main part. Classification of accuracy is dependent on segmentation results. Accuracy of classification is measured using precision rate and recall rate.

When we classify the results, the stone identification provides a lower precision and recall rate. White cereal’s color and texture of stone are most similar to each other. Due to this, there is a classification problem of stone images. The improvement requires increasing the precision and recall rate.

There is a constant distance between the cereals sample and the camera in the acquiring image steps. The output of the module is evaluated for different distances. The purpose of this process is to identify the optimal distance between the camera and the cereals sample. For the segmentation of cereals seeds, the evaluation is done. In Table 3, evaluation results for the different distances between the camera and cereals sample are mentioned.

For the highest F measure value, the distance is 15 cm. The selected distance covers an area that can spread about 300 cereals seeds. Therefore, 15cm is selected as the optimistic difference between the cereals sample and the camera. For the image acquiring process this distance is used.

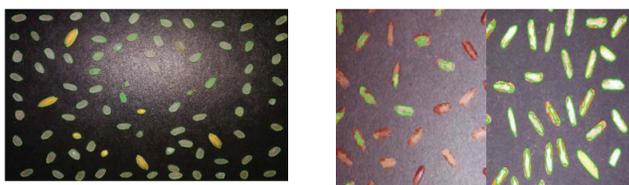


Fig 5. a)Incorrectly segmented cereals sample images; b)Effect of Non Uniform Light Distribution

Table 2. Evaluation results of Classification

Classification Class	Precision Rate (%)	Recall Rate (%)	F measure (%)
Rice	99.75	94.85	99.07
Wheat	96.04	85.84	88.03
Sorghum	97.57	96.38	96.62
Millet	54.89	80.82	51.64

Table 3. Evaluation results for different Distance between camera and cereals sample

Distance	Precision Rate (%)	Recall Rate (%)	F Measure (%)
9cm	70.58	84.70	76.99
12cm	88.99	85.84	87.39
15cm	91.62	93.18	92.39
18cm	90.74	87.00	88.33
21cm	90.53	88.27	89.38

The mathematical formula of support vector machine (SVM) is given by,

$$\frac{1}{n} \sum_{i=1}^n (1 - y_i f(x_i))_+ + \lambda \|h\|_{H_k}^2 \tag{4}$$

Where,  $(x)_+ = \max(x, 0)$  and  $\| \cdot \|_{H_k}$  denotes the square norm of the function h.  $H_k$  is the homogeneous linear function.  $\lambda$  is the tuning parameter.

The mathematical formula of multi-support vector machine (MSVM) is given by,

$$\frac{1}{n} \sum_{i=1}^n L(y_i) \cdot (f(x_i) - y_i)_+ + \frac{1}{2} \lambda \sum_{j=1}^k \|h_j\|_{H_k}^2 \tag{5}$$

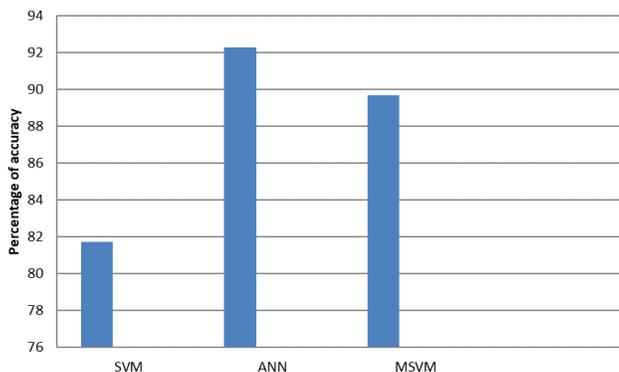
Compare to equations (4) and (5), we can observe that the support vector machine is used only for two classes, while the multi-support vector machine is used for more than two classes.

### 3.2 Comparative Analysis of ANN, SVM AND MSVM

Here we have evaluated the cereals grain classification with ANN, SVM and MSVM. We have extracted features for the proposed ANN and MSVM algorithm.

**Table 4.** Comparative analysis of ANN, SVM AND MSVM

No of Images	Type of classifier	Train : Test	Accuracy
48	ANN	70:30	92.3%
48	SVM	70:30	81.7%
48	MSVM	70:30	89.7%



**Fig 6.** Comparison Analysis of SVM/ANN/MSVM

In comparison to the study made by<sup>(10)</sup>, the previous author used the svm algorithm. But it has limitations if it’s not acceptable for large data sets. It does not execute very well when the data set has more sound i.e. target classes are overlapping. In cases where the number of properties for each data point outstrips the number of training data specimens, the support vector machine will underperform

To overcome the limit of svm in our system we use a multi class support vector machine. But it has some limits: Multi class classification is the problem of classifying instances into one of three or more classes. While many classification algorithms naturally permit the use of more than two classes, some are by nature binary algorithms; these can, however, be turned into multi class classifiers by a variety of strategies<sup>(5)</sup>.

The previous study is based on ANN and SVM. It defines only a single classification of cereal. SVM is used for single cereal grains classification and has limited features. SVM has only two classes. Due to this limitation, the accuracy of SVM is degraded compared to the proposed MSVM technique. The current scenario is multigrain classification. To overcome the performance of SVM, we have proposed the MSVM technique for multigrain classification. In the MSVM technique, we have incorporated more features. MSVM is a better technique for multi-class grain classification. We have also compared the results of MSVM, and ANN with the SVM technique.

## 4 Conclusion

In this research study, the classification of the cereals grain sample system has been investigated using various techniques. There are eight different features are extracted from cereal grain samples. The features are area, centroid, major axis length, minor axis length, orientation, eccentricity, convex area, and perimeter. In addition, the neural network and multi-support vector machine classify the cereal grain features. These methods are useful for six databases of cereals like rice, barley, millet, sorghum, wheat, and mille. Its main role in the valuation of the planned system performance. We have achieved an accuracy of 92.3% in the neural network classifier. The proposed methods can achieve high performance. In the future, we have applied more features and algorithms for better classification.

## 5 Future Scope

The proposed methods are able to achieve high performance, but there are some issues that still make it difficult to achieve better performance such as type of databases and quality images in these databases and also, the techniques that are used in preprocessing stage. However, a few recommendations are acquainted below in order to enhance the performance of the proposed system, for example

- Applying the proposed system on different databases.
- Using other feature extraction techniques.

## 6 Acknowledgement

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## References

- 1) Çelik Y, Başaran E, Dilay Y. Identification of durum wheat grains by using hybrid convolution neural network and deep features. *Signal, Image and Video Processing*. 2022;16(4):1135–1142. Available from: <https://doi.org/10.1007/s11760-021-02094-y>.
- 2) Singh H, Rawat CS, Verma D. Image Processing Techniques for Analysing Food Grains. *2019 3rd International Conference on Computing Methodologies and Communication (ICCMC)*. 2019. Available from: <https://doi.org/10.1109/iccmc.2019.8819760>.
- 3) Sowmya BJ, P N. A Convolution Neural Network-Based Wheat Grain Classification System SeemaShedole. *Journal of Scientific Research*. 2022;66(2). Available from: [https://bhu.ac.in/research\\_pub/jsr/Volumes/JSR\\_66\\_02\\_2022/4.pdf](https://bhu.ac.in/research_pub/jsr/Volumes/JSR_66_02_2022/4.pdf).
- 4) Afaq AS, Shah, Haoluo, Putuditapickupana A, Ekeze, Ferdousohel H, et al. Automatic and fast classification of barley grains from images: A deep learning approach. *Smart Agricultural Technology*. 2022;2. Available from: <https://doi.org/10.1016/j.atech.2022.100036>.
- 5) Tin KMM, Mon EL, Win S, Suhlasing S. Myanmar Rice Grain Classification Using Image Processing Techniques. *International Conference on Big Data Analysis and Deep Learning Applications(ICBDL)*. 2019;p. 2019–2019. Available from: [https://doi.org/10.1007/978-981-13-0869-7\\_36](https://doi.org/10.1007/978-981-13-0869-7_36).
- 6) Khatri A, Agrawal S, Chatterjee JM. Wheat Seed Classification: Utilizing Ensemble Machine Learning Approach. *Scientific Programming*. 2022;2022:1–9. Available from: <https://doi.org/10.1155/2022/2626868>.
- 7) India rank in the exportation of Basmati rice 2019. . Available from: <http://www.worldstopexports.com/rice-exports-country/>. Accessed.
- 8) Ibrahim S, Kamaruddin SBA, Zabidi A, Ghani NAM. Contrastive analysis of rice grain classification techniques: multi-class support vector machine vs artificial neural network. *IAES International Journal of Artificial Intelligence (IJ-AI)*. 2020;9(4):616–616. Available from: <https://doi.org/10.11591/ijai.v9.i4.pp616-622>.
- 9) Sieve analysis of circular seeds. p. 8–10. Available from: [retsch.com/applications/knowledgebase/sieveanalysis/](https://www.researchgate.net/publication/354811111/Sieve_analysis_of_circular_seeds) Accessed.
- 10) Ibrahim S, Zulkifli NA, Sabri N, Shari AA, Noordin MRM. Rice Grain Classification using Multi-class Support Vector Machine (SVM). *IAES International Journal of Artificial Intelligence (IJ-AI)*. 2019;8(3):215–215. Available from: <https://doi.org/10.11591/ijai.v8.i3.pp215-220>.
- 11) Cinar I, Koklu M. Classification of Rice Varieties Using Artificial Intelligence Methods. *International Journal of Intelligent Systems and Applications in Engineering*. 2019;7(3):188–194. Available from: <https://doi.org/10.18201/ijisae.2019355381>.