

Detection of Foreign Materials in Wheat Kernels using Regional Texture Descriptors



Neeraj Julka, A.P Singh

Abstract: *The present paper reports the development of an efficient machine vision system for automatic detection of foreign materials in wheat kernels using regional texture descriptors. In this system, the detection task is performed in two phases. These phases include features extraction phase followed by classification phase. New surface texture descriptors of wheat kernels are developed using Non-Shannon entropies in this work. These entropies are defined using intensity histograms of wheat and non-wheat regions in the given image. Such an attempt has not been made earlier. Experimental results on a database of about 2635 wheat and non-wheat components from 63 images confirm the effectiveness of the proposed method. The classification task is performed by the neural classifier in the proposed machine vision system. An accuracy of more than 98.5% is achieved using proposed system. However, the results of present investigations are quite promising.*

Keywords: *Wheat, non-wheat, kernel, texture, machine vision, quality and recognition.*

I. INTRODUCTION

Human-eye based visual inspection of wheat kernels is the only method that has been used extensively till-date in commercial environment for the assessment of wheat quality[1]. However, this manual method is time consuming, labour intensive and inconsistent and the results are not reliable due to human errors and/or inexperienced technicians [2]. In order to circumvent these problems, there is an urgent need to develop some machine vision based systems for automatic inspection of wheat quality. The emergence of Electronic-Marketplace (E-Marketplace) supported on the architecture of Internet of Things (IoT) technology, has facilitated the farmers to have on line sale of their products[3]. However, this in turn has necessitated to develop urgently on-line inspection systems of agriculture produce. However, machine vision technology if developed suitably can very well serve this purpose. In line with such requirements, the present work has been carried out. The proposed on-line machine vision system will definitely serve as an important module in such a newly emerged marketplace. In this respect, a comprehensive review of major applications of machine vision is available for grain quality evaluation illustrating explicitly different system components, image processing & analysis techniques, advantages and limitations [4].

This review concludes that machine vision system provides rapid and accurate information about external quality attributes of food grains. However, it has been further observed that the performance of these machine vision systems is determined primarily by the effectiveness of the classification task executed in the same[5]. In this context, the main aim of the present work is also to develop an efficient classifier module using Artificial Neural Network (ANN) for recognition of foreign material in wheat kernels in the proposed machine vision system. Literature survey in this regard further indicates that three types of classifiers are reported till-date for machine vision based recognition of foreign material in wheat kernels[6]. These classifiers are named as statistical classifier[7], discriminant classifier[8] and Artificial Neural Network (ANN) based classifier[9], [10]. However, these classifiers are implemented using a large number of input features set for making the distinction between different classes, thus making the same very complicated. In order to address this issue, the present study reports on the development of an efficient classifier based on artificial neural network trained with a small number of textural features as input for identification of foreign material in non-touching wheat kernels. The proposed classifier is executed using Levenber-Marquardt learning algorithm which ensures its faster training[11]. Foreign component used in the present work includes other grains as well as other grain and dockage components.

II. LITERATURE REVIEW

A number of studies have been conducted in the recent past in context of formulating the underlying principle and theoretical framework for the development of proposed machine vision system. In fact, these studies are not conducted explicitly for the development of an integrated machine vision system as a flowing pipeline exclusively for quality inspection of wheat. However, these studies as reviewed in the next section establish the underlying principle for establishing a flowing pipeline of an automated machine vision system for quality inspection of wheat.

(a) Models With 230 Features:

A set of algorithms was proposed to extract 230 features including 51 morphological, 123 color and 56 textural features from captured images of five different grain types and dockage constituents [7]. In this work, different morphological, color, texture and combination models were evaluated for classification performance using neural network classifier. In another work, the influence of growing location using statistical comparison method was also examined with respect to training and classification performance in which a total 230 features were extracted including 51 morphological, 123 colour and 56 textural features from colour images of Canada Western Red Spring (CWRS) wheat kernels[10].

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This study reveals that most of the image features from different growing locations had significant differences but the same did not affect the grain classification performance as tested by detecting foreign material represented by barley [10] exclusively. In this work, only barley has been included as the foreign material in the wheat sample and no other foreign material was considered. Moreover, the study has been carried out to examine the effect of different growing locations on the wheat kernels.

(b) Models With 335 Features:

In this context, another work is reported in which 51 morphological, 93 colour, 56 textural and 135 wavelet features were extracted from color digital images of non-touching kernels of Canada Western Red Spring (CWRS) wheat, Canada Western Amber Durum (CWAD) wheat, barley, oats, and rye by means of an area scan camera[12] for classification using statistical classifiers. This study further concluded that combining all morphological, colour, textural and wavelet features gave the best classification using the linear discriminant classifier with a classification accuracy of 99.4% for CWRS wheat, followed by 99.3%, 98.6%, 98.5%, and 89.4% for rye, barley, oats and CWAD wheat respectively[12]. However, neither dockage component such as chaff, straw and stone has been included in this study nor machine vision system was developed. Moreover, these features were extracted for characterization of wheat kernels using standard image processing software.

(c) Model With 150 Features:

Also, a set of algorithms were also developed to acquire and process color images from bulk grain samples of five types namely barley, oats, rye, wheat and durum wheat[9]. The developed algorithms were used to extract over 150 color and textural features and a back propagation neural network-based classifier was developed to identify the unknown grain types using, color and textural features leading to classification accuracies of over 98% for all grain types[9]. In this study, bulk grain samples were considered without having any characterization of the individual kernels. Moreover, no machine vision system was reported

(d) Model With 32 Features:

Wheat class identification by bulk sample analysis was also proposed in another work using machine vision method, in which, a monochrome camera was used to identify eight western Canadian wheat classes at four moisture levels (11%, 14%, 17% and 20% wet basis) by bulk sample analysis (n ¼ 100 images for each group of samples) using 32 textural features[13]. This study does not consider unconnected wheat kernels and it is also merely based on bulk wheat samples.

(e) Model With 18 Features:

Another digital image analysis algorithm was also reported based on color features to classify individual kernels of Canada Western Red Spring (CWRS) wheat, Canada Western Amber Durum (CWAD) wheat, barley, oats, and rye, in which eighteen color features (mean, variance and range of red component, green component, blue component, hue component, saturation component and

intensity component) were used for the discriminant analysis [14]. In this work, grains from 15 growing regions (300 kernels per growing region) were used as the training data set and another five growing regions were used as the test data set. When the first 10 most significant color features were used in the color model and tested on an independent data set (the test data set where total number of kernels used was 10500, for CWRS wheat, 300 kernels each were selected for three grades), the classification accuracies of CWRS wheat, CWAD wheat, barley, oats, and rye were 94.1, 92.3, 93.1, 95.2, and 92.5%, respectively. When the model was tested on the training data set (total number of kernels used was 31500), the classification accuracies were 95.7, 94.4, 94.2, 97.6, and 92.5%, respectively, for CWRS wheat, CWAD wheat, barley, oats and rye [14].

(f) Combined Morphological And Color Features Models:

Algorithms were also developed in another work to classify dockage components from Canada Western Red Spring (CWRS) wheat and other cereal grains (e.g. durum wheat, barley, rye and oats) based on morphology and colour based exclusive models as well as combined morphology-colour models. These models were evaluated for classifying the dockage components with mean accuracies of 89.4%, 71.4% and 93.2% respectively, when tested on the independent test data sets using holdout non-parametric classifier[15]. In this work, the dockage classes used include wheat heads, chaff, wild oats, canola, wild buckwheat, flax, and broken-wheat pieces and developed algorithms were tested on images taken with an area scan camera. In this work, However, in this work, accuracy achieved is very limited.

Thus, the above review clearly establishes that statistical methods remain the primary learning methods in the field of computer vision for food quality evaluation. Intelligent classifiers are rarely learnt or reported. Similarly, machine vision systems are also rarely reported. The reported studies are basically carried out to characterize the wheat kernels using standard image processing software without considering any development towards the integrated machine vision system. However, in the present work, an attempt has been made to develop complete machine vision system while considering each and every component of the same individually. However, among the applications of learning algorithms in computer vision for food quality evaluation, most of them are for classification and prediction, however, there are also some for image segmentation and features selection. It is also observed that texture provides important characteristics for object identification in a digital image. In line with this strategy, accordingly, this paper presents the results of using digital image processing algorithm in combination with machine learning and pattern recognition to measure the textural features of unconnected wheat kernels as well as classify them accurately into wheat and non-wheat categories for the purpose of quality inspection. The samples used in non-wheat components including foreign material are stones, straw, chaff, rice, black chickpea, white chickpea, rye and barley.

III. METHODOLOGY

3.1 Image Acquisition

A CCD (Charge Coupled Device) based digital color camera by Basler Vision Technologies having 1392×1040 resolution (model Basler scA-17fc) is used in the present work to acquire images of unconnected wheat kernels containing foreign material as well. This camera is interfaced to Personal Computer through high speed IEEE 1394b interface and is mounted on a stand, which provided easy movement and stable support to it. For the ease of capturing images, camera is mounted on the topside of the setup to cover the entire area of capturing image. In order to correct the non-uniform illumination, LED light is used to spread the light on the object in a uniform manner. To analyze the wheat kernels in variable light, regulator is also provided with the simple lamps to control the amount of light falling on wheat and is measured from time to time by LUX meter.

3.2 Grain Samples Preparation

There is no standard dataset of wheat is available so created own dataset for training and testing. Dry grain samples of different varieties of wheat materials used in the experiments were obtained from the Akal Academy, Mustuana Sahib, District Sangrur, Punjab, India. In the experimental investigation, however, only sound, wholesome and good kernels of nine different varieties of wheat as selected through visual inspection were used. Sub-samples of each grain type to be used in imaging were obtained by dividing the larger sample. The sub-samples were placed manually on a viewing plate to avoid the non-touching of two or more components. The kernels orientation was not controlled or fixed. The orientation of the components for camera viewing was random in nature. The kernels of wheat and non-wheat components were, however position manually in non-touching manner. The images were labeled for identification of each region in the image. The algorithm was used to find the contour of each component. Sixteen morphological features based on texture[12] were extracted and computed. Morphological

(Texture) features, the most common measurements that are made on given objects are those that describe texture quantitatively. In fact, texture features are physical measures that characterize the appearance of grains. The morphological features extracted in the proposed work from wheat and non-wheat regions in the image include computation of surface texture using Intensity Histogram[16] as well as Gray Level Concurrence Matrix [16].

3.3 Image Pre-Processing

The present research work involves automatic detection of foreign materials in wheat kernels using regional texture features based pattern recognition. Pattern recognition leads to very convincing results in some specific industrial applications. At the same time, the performance does not reach the expected value in other fields. However, in all these cases, the system used for image acquisition, is a factor, which has an influence on this quality of results. Other factors related on the lighting and the nature and characteristics of the objects to be recognized has also their influence. In the field in which we are interested, the recognition rate of wheat and non-wheat components based on texture descriptors is 98.5%. However, the results may be improved with careful choice of these devices and systems. The images, taken whatever the orientation and the faces of wheat and non-wheat components, are preprocessed before the operation of feature extraction. This preprocessing consists in applying an average filter [16], an image binarization using Otsu’s algorithm[16] and texture features extraction. Figure.1 shows examples of original and pre-processed images. This work deals with an automatic wheat kernel analysis system based on pattern recognition method. However, this paper emphasizes only the pattern recognition aspect of the problem and in our case, seven different types of impurities are considered along with wheat kernels. The recognition procedure is executed on the basis of regional texture descriptors. The proposed method has given very good results with small confusion rate. After image acquisition and their pre-processing, the general process includes extraction of regional features followed by classification using neural classifier[9].

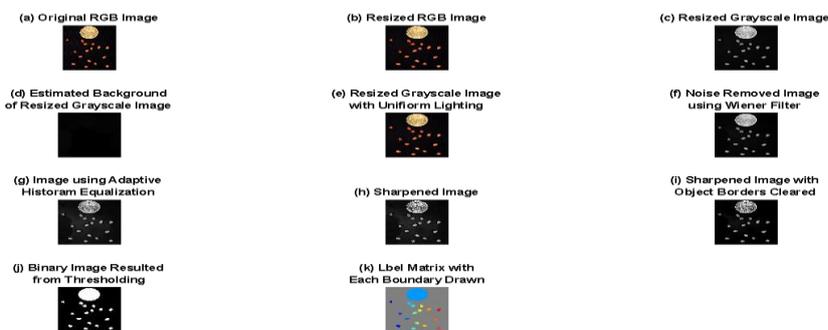


Figure.1 Example of Original and Pre-Processed Images

3.5 Texture Features Extraction

Texture analysis is fundamental in many industrial applications including automated machine vision based inspection of wheat and other cereal grains. Regional texture features, the most common measurements that are made on given objects are those that describe object appearance[16]. In fact, these features are used to characterize the appearance of wheat and non-wheat components in a given digital image quantitatively. The regional texture features extracted in the present work are categorized into three categories depending upon method of computation: (i) Conventional surface texture features computed from Intensity Histogram [16] of a Region including Shannon entropy (ii) New surface texture features of a region computed from Intensity [17] Histogram (iii) surface texture features of a region computed from Gray Level Concurrence Matrix [17]. However, such an attempt has not been made in this respect till-date. All the conventional surface Texture Descriptors Computed from Intensity Histogram of a Region extracted in the present work are indicated in Table1. These

include mean, standard deviation, smoothness, third moment, uniformity, and Shannon-Entropy. Based on these descriptors, it is possible to make a distinction between wheat and non-wheat component regions in the given digital image. Similarly, Surface Texture Descriptors Computed from Intensity Histogram of a Region using Non-Shannon Entropies are also indicated in Table-2. In a similar way, Surface Texture Descriptors Based Computed from Gray Level Concurrence Matrix of a Region are Gray level concurrence matrix is computed from the segmented region occupied by each wheat and non-wheat component in the image. Then, various specified properties of a gray-level concurrence matrix are computed including contrast, homogeneity, correlation and energy as indicated in Table-2. Based on these descriptors, it is established that it is possible to make a distinction between wheat and non-wheat component accurately and uniquely in the given digital image.

Table-1
Surface Texture Descriptors Based on Intensity Histogram of a Region [16] including Shannon Entropy

S. No.	Texture Descriptor (Moment)	Mathematical Expression	Definition
1	Mean	$m = \sum_{i=1}^{L-1} z_i p(z_i)$	Measure of Average Intensity
2	Standard Deviation	$\sigma = \sqrt{\mu_2(z)}$	Measure of Average Contrast
3	Smoothness	$R = 1 - \frac{1}{1 + \sigma^2}$	Measure of relative smoothness of the intensity in a region.
4	Third Moment	$\mu_3 = \sum_{i=0}^{L-1} (z_i - m)^3 p(z_i)$	Measure the skewness of a histogram.
5	Uniformity	$U = \sum_{i=0}^{L-1} p^2(z_i)$	Measure Uniformity
6	Entropy (Shannon)	$S = - \sum_{i=1}^L p_i \log \log (p_i)$	Measure of degree of randomness

Table-2
Surface Texture Descriptors Based on Intensity Histogram of a Region using Non-Shannon Entropies [17]

S. No.	Texture Descriptor	Expression	Remarks
1	Kapur Entropy	$K_{\alpha, \beta} = \frac{1}{\beta - \alpha} \log \frac{\sum_{i=1}^n p_i^\alpha}{\sum_{i=1}^n p_i^\beta}$ $\alpha \neq \beta, \alpha > 0, \beta > 0$	Measure of degree of randomness of normalized Gray Level Co-occurrence Matrix (GLCM) of the ROI using Kapur Entropy.
2	HC Entropy	$HC = \frac{1}{1 - \alpha} \left(\sum_{i=1}^n p_i^\alpha - 1 \right)$ $\alpha \neq 1, \alpha > 0$	Measure the degree of randomness of normalized Gray Level Co-occurrence Matrix (GLCM) of the region of interest using Havrda & Charvat Entropy
3	Tsallis Entropy	$H_q(P) = \frac{1}{\alpha - 1} \left[1 - \sum_{i=1}^n p_i^\alpha \right]$ $\alpha \geq 0, \alpha \neq 1$	It is useful for describing the properties of non-extensive systems entropies.
4	Renyi Entropy	$R = \frac{1}{1 - \alpha} \log \left(\sum_{i=1}^n p_i^\alpha \right)$ $\alpha \neq 1, \alpha > 0$	It is two dimensional entropy obtained from two dimensional histogram to get better accuracy while maintaining overall functionality.
5	Collision Entropy	$C = -\log \left(\sum_{i=1}^L p_i^2 \right)$	It is compiled as piety of a given probability distribution and provides secondary information about importance of specific events.
6	Min Entropy	$M = \min (-\log A = \pi r^2)$	Smallest measure in family of Renyi entropies, where goal is to determine probability that the prediction of random variable is difficult.

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$$[OW] = \left[\begin{matrix} ow_{11}ow_{12}ow_{13}.....ow_{1m} \end{matrix} \right] \quad (4)$$

$$[UB] = \left[\begin{matrix} ub_1 \\ ub_2 \\ \cdot \\ ub_n \end{matrix} \right] \quad (5)$$

$$[VB] = \left[\begin{matrix} vw_1 \\ vw_2 \\ \cdot \\ vw_m \end{matrix} \right] \quad (6)$$

$$[OB] = [ob] \quad (7)$$

The Mean Square Error (MSE) that is the performance index[11]is given by

$$MSE = \frac{1}{n} \sum_{i=1}^n [x_i - F_{ANN}(z_i)]^2 \quad (8)$$

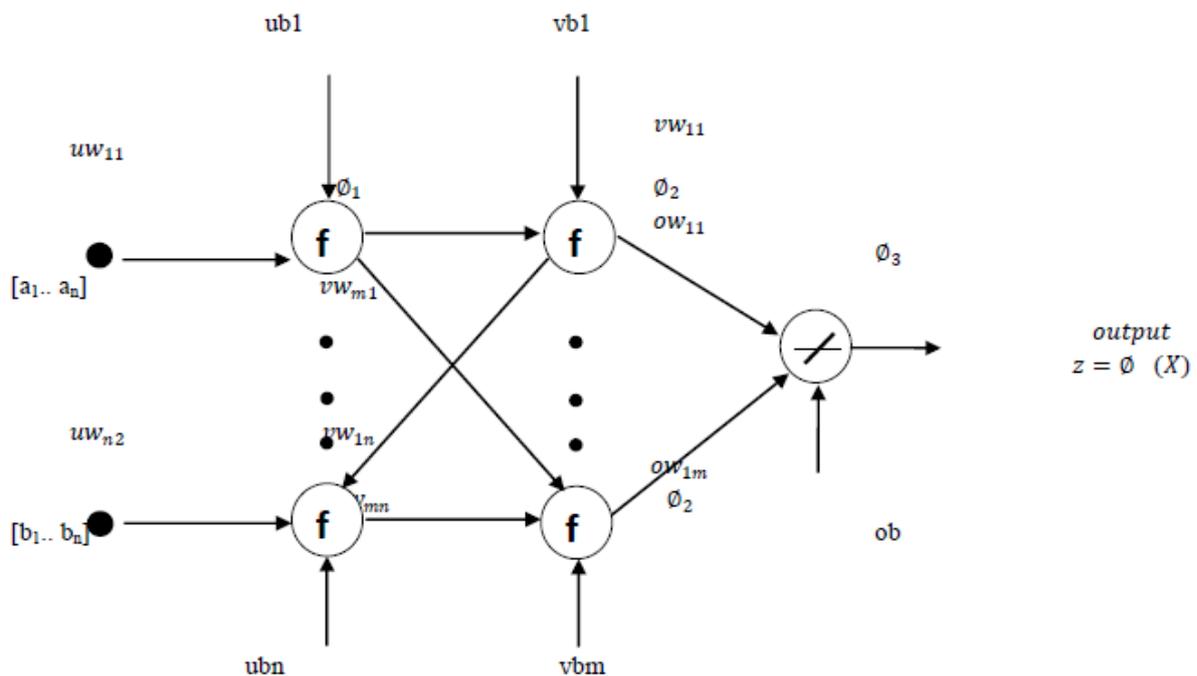


Figure 9 Typical Neural Paradigm Structured in Layers of Neurons[20]

Table-1
Estimated Value of the different entropies

S. No.	Entropy	Grain Kernels				Non-Grain Components			
		Wheat	Oat	Barley	White Chickpea	Black Chickpea	Chaff	Straw	Stone
1	Shannon	5.5752	4.9543	3.5921	5.7662	3.4596	5.3110	6.5798	6.5941
2	Kapur	7.0141	5.6944	6.7616	5.1424	4.5673	7.0951	7.4239	7.4215
3	Renyi	5.3653	4.9032	4.6106	5.0273	3.6620	5.1241	5.7284	5.7275
4	HC	65.6226	59.3451	45.6148	56.3154	29.7866	61.0707	77.4857	77.4535

Table-2 Estimated Value of the GLCM Texture components

S. No.	Texture	Grain Kernels				Non-Grain Components			
		Wheat	Oat	Barley	White Chickpea	Black Chickpea	Chaff	Straw	Stone
1	Contrast	0.4632	0.3902	0.1602	0.2533	0.7429	0.1687	0.2386	0.2457
2	Correlation	0.9704	0.9834	0.9891	0.9787	0.7707	0.9884	0.9791	0.9785
3	Energy	0.2108	0.3945	0.4454	0.2922	0.3508	0.2713	0.1335	0.1339
4	Homogeneity	0.9316	0.9424	0.9703	0.9601	0.8560	0.9617	0.8974	0.8973

Table-3 Estimated Value of the texture features of segmented component

S. No.	Moments features	Grain Kernels				Non-Grain Components			
		Wheat	Oat	Barley	White Chickpea	Black Chickpea	Chaff	Straw	Stone
1	Average gray	151.3418	140.4532	71.2457	141.499	39.7041	112.1139	144.3609	144.2784
2	Standard Deviation	95.2184	94.5634	93.5674	83.4493	46.0550	93.5142	82.2182	82.24
3	Smoothness	0.1224	0.1090	0.1187	0.0967	0.0316	0.1108	0.0942	0.0942
4	Third Moment	-10.9075	-9.0353	7.5024	-9.1543	-3.2676	-3.2676	-7.3735	-7.3163
5	Uniformity	0.0672	0.5903	0.3850	0.0722	0.1525	0.1525	0.0497	0.0497
6	Entropy	5.9440	5.5323	3.3703	5.2842	5.1096	5.1096	6.3796	6.3820

IV. RESULTS AND DISCUSSION

The data sets computed for the range of different textural features of different types grains including foreign material chosen for present investigation are given in Tables-1, 2 and 3. To assess the pattern classification ability of the proposed neural algorithm using sixteen morphological textural features, 16-10-1 structure of Artificial Neural Network (ANN) trained with Levenberg-Marquardt learning algorithm was used to classify the kernels into wheat and non-wheat components. This proposed ANN structure is based on the architecture of feed-forward back-propagation network. All the above mentioned six features extracted were used as the input to the neural network. In Table-IV shows the MSE and Correlation Coefficients for estimating the wheat and non wheat components as a result of training, validation and test study. In Table-IV shows the attribute, input, output, hidden layers neurons, epochs and MSE in estimating the wheat and non wheat components as a result of training, validation and test study. It shows the number of samples for training phase, test phase and validation phase. The total samples were 300 out of which were divided randomly for each study and its corresponding values of MSE and Correlation Coefficients are approximately equal to 1. The confusion matrix for a cross validation for a four way discrimination into wheat, non-wheat and foreign materials is also given in Table-V. It shows the texture as a attribute for estimating the wheat and non wheat samples. The total samples were 300 out of which were divided randomly for each study and input layers for this Network are sixteen are and only one target was there to identify whether the wheat or non wheat samples. In the confusion matrix plot, the rows correspond to the predicted class (Output Class), and the columns show the true class (Target Class). The diagonal cells show for how many (and what

percentage) of the examples the trained network correctly estimates the classes of observations. That is, it shows what percentage of the true and predicted classes match. The off diagonal cells show where the classifier has made mistakes. The column on the far right of the plot shows the accuracy for each predicted class, while the row at the bottom of the plot shows the accuracy for each true class. The cell in the bottom right of the plot shows the overall accuracy. Generally, the error reduces after more epochs of training, but might start to increase on the validation data set as the network starts over-fitting the training data. In the default setup, the training stops after six consecutive increases in validation error, and the best performance is taken from the epoch with the lowest validation error. The Learning characteristics of proposed MLFFBP-ANN based model for estimating wheat and non wheat, trained with Levenberg Marquardt training algorithm is shown. The plot shows the mean squared error of the network starting at a very large value and decreasing to smaller value. In other words, it shows that the network is learning. The plot has three lines, 314 samples are used for training, 68 samples used for testing and 68 samples used for validation. Six vector are used to validate how well the network generalized. Training on the training vectors continues as long the training decreases the mean square error(MSE) on the validation vectors. After the network realizes the training set training is stopped. Finally, that the network has never seen. It has been only observed that the total number of only 37 epochs are needed to reduce the MSE level to a low value of 0.0078224. Achievement of this low value of MSE indicates the trained model is an accurate model of detecting wheat and non wheat components.

Table-4 Detection Accuracy using Regional Texture Descriptors Based Neural Classifier

Valid Accuracy	Average Confusion Matrix			All Grain Accuracy
100%		Grain	Impurity	98.5%
	Grain	100%	0	
	Impurity	98.5%	1.5%	

V. CONCLUSION

The presented study was conducted to develop a machine vision system for identification and detection of wheat and non-wheat components. The study is also relevant in the context of the development of a comprehensive automated grading system of grains. The objective of the study was to determine the discriminating ability of morphological textural features for identification of wheat and non-wheat seeds. The non-wheat components investigated in the present study include rice, black chickpea, white chickpea, rye and barley. However, the foreign materials chosen were straw, chaff and stones. The novelty of the present work is to demonstrate the use of artificial neural network based classifier trained with faster learning methods using reduced number of textural features of unconnected kernels using non-Shannon measure of entropy. The new texture features reported in the present work have potential future in the field of automated machine vision based inspection of agriculture produce.

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