INDIAN WHEAT SEED CLASSIFICATION BASED ON TEXTURE ANALYSIS USING ANN

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Abstract- Aid of computer (machine) vision techniques is an accusative method which will helpful in online verification and in stepping up the accuracy of wheat seed classification in real applications of agricultural industry. The study contains the evaluation of how efficiently relegate the wheat seed types of most effective texture features group through the examination of distinct texture features of wheat seed species images. Including all, there were 60 gray scale images of bulk wheat seed species were taken under the standardized illumination condition (fluorescent light).There are 131 textural features were educed from six numbers of matrices namely LBP(local binary pattern),LSN(local similarity number),LSP(local similarity pattern),gray level, GLRM (gray level run-length matrix) and GLCM (gray level co-occurrence matrix).The substantial textural features were ranked with the use of stepwise discrimination process. This process was severally used for each matrix and features of all matrices simultaneously as well. The artificial neural network (ANN) was used for the classification of wheat seed. The percentage of average accuracy of classification result was 76% when selective 60 features were considered.

Keywords- Texture features, ANN, LSN, LBP, LSP, Gray, GLRM, GLCM.

I. INTRODUCTION

In planting situation, where different classes of grain are supposed to be planted in a big field, practically the quick recognition is needed. In order to increasing the quality and quantity of harvest in wheat planting, important thing is to use confirmed seeds. For the same different methods are expanded based on computer visions. The implementation of new methods for reliable and fast identification and classification of seeds is of major technical and economical importance in the agricultural industry.

There is lots of wheat seed varieties planted in India and each has its own customer and application. Thus, the variety confirmation is a very significant step before planting. The determination of wheat classes is done with skillful experts who identify the varieties based on their visual characteristics. But this the subjective approach and mistakes, like different results from different experts, are not avoidable. Therefore an objective approach like machine vision can prevent these errors and improve the wheat seed selection and verification in actual applications.

As per the ocular inspection, the automatic classification of seeds should be based on knowledge of seed size, shape, color and texture. Therefore, it is necessary that these parameters should be used by machine vision for reorganization of different objects from each other. By assessing the discriminating power of these characteristics for the unique identification of seeds i.e. quality seed from many seed species one can develops very effective computer vision system. Till today, many researchers to identify the cereal grain class have used machine vision methods [1]-[3]-[4]-[5]. Textural, color and morphological features have been extracted from images and different classifiers have been employed to recognize the grain samples [1]-[3]-[5].

It was observed that besides color and morphology of wheat seed species its textural features are more effective for its classification techniques. In this paper, Indian wheat seed variety identification and their classification efficiency of a machine vision algorithm which analyzes effective textural features of the bulk samples was evaluated. To extract textural features from grayscale images we first converted the gray image into six matrices namely gray matrix, LBP (local binary pattern), LSP (local similarity pattern), LSN (local similarity number), GLCM (gray level co-occurrence matrix), and GLRM (gray level run length matrix).

II.RELEVANT WORK

The study contents [1]-[5] over the past few years, many of the researchers have evaluated the capabilities of machine vision algorithms for wheat variety recognition [3] and quantified the shape variation in 15 Indian wheat varieties using custom-built software. In wheat seed classification studies, some studies reported the use of textural features though its color and morphological features are principally used for this application. The imaging condition has also a significant impact on the classification efficiency. For variety identification various illuminations techniques had been employed [3]-[5].

This paper is organized as follows. First, the hardware and the experimental conditions for image acquisition were described. Second, total 131Textural

features of gray images of each wheat seed species were extracted and the measurement of textural parameters is defined. In last section results are discussed and few conclusions drawn from the obtained results.

III. METHODOLOGY

The proposed work in this paper is to extract the textural features of different types of wheat seed species which are further used for their classification. For this, primary requirement is taking number of images of each type of grain samples.

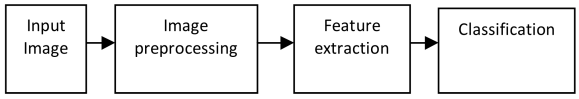

Fig.1 Block diagram of the proposed approach

A. Samples of grain varieties

In this paper three Indian wheat varieties (Lokvan Gujrat, Lokvan MP, MP sure, Khapali) are considered. The images of wheat seed species were taken from fixed distance under the same illumination conditions.

B. Sample Image acquisition

Fifteen images of each varieties were taken (total 60 images).Images were cropped to lower resolutions. By shaking a small container, the seed samples were leveled. On imaging stand a fluorescent ring light was mounted above the bulk samples for imaging.

C. Textural algorithms

Instead of extracting textural features from gray level images of sample wheat seeds, various matrices were produced from the gray level images. The matrices were GLCM (gray level co-occurrence matrix), GLRM (gray level run length matrix), LBP (local binary patterns), LSP (local similarity patterns) and LSN (local similarity numbers) and textural features were extracted from these matrices.

As per the statistical texture analysis, texture features are computed from the statistical distribution of observed combinations of intensities at specified positions relative to each other in the image.

a. LSP (Local similarity patterns)

LSP is a rotational invariant descriptor. In it for the threshold process a specified value of similarity range radius (SRR) is used. If the absolute difference between each 3× 3 neighborhoods and the value of the central pixel is less than SRR value, then the value of 1 is to be placed into the neighborhood pixel otherwise value of 0 is to be placed.

Then the binary values of the threshold neighborhood are mapped into 8-bit binary numbers in clockwise order. Eight different binary numbers are produced started from eight possible points. Among the equivalent decimal numbers produced, the maximum one describes the rotation invariant LSP of that particular neighborhood.

b. LSN (Local similarity number)

It is also a rotational invariant descriptor. LSN also counts the difference between 3×3 neighborhood values and center pixel. Further if these values are less than specified SRR values then corresponding neighborhood pixel gets value of 1 otherwise value of 0.The final step is calculate the sum of all the threshold neighborhoods and obtain value of central pixel. Hence there are total nine possible values (0-8) from 3×3 neighborhood using LSN process.

c. LBP (Local binary patterns)

In the basic LBP procedure, each 3×3 neighborhood is threshold with the central pixel value. These threshold neighborhood values are multiplied by weights given to corresponding pixels. At the final step the resulted values are summed. The number got from the summation is the number of this texture unit.

For illumination changes and computational simplicity LBP operator has considerable tolerance against them. This one is one of the most important properties of LBP operator.

d. GLCM (Gray level co occurrence matrix)

The GLCM is a tabulation of how often different combinations of pixel brightness values (grey levels) occur in an image. According to the number of pixels (intensity points) in each combination, statistics are classified into first-order, second order and higher-order statistics. The Gray Level Co-occurrence Matrix (GLCM) method is a way of extracting second order statistical texture features.

e. GLRM (Gray level run length matrix)

Gray level run is defined as a set of consecutive, collinear pixels having the same gray level. Eleven texture descriptors are calculated to capture the texture properties and differentiate among different textures.

D. Feature extraction methods

The 131 numbers of textural features of each monochrome image of the bulk wheat seeds samples were extracted. These features includes 32 gray level textural features, 31 LBP features where 25 features were histogram groups , 31 LSP features in which 25 features were histogram groups, 15 LSN features where nine features were histogram groups , 10 gray level co occurrence matrix (GLCM) features and 12 gray level run-length matrix GLRM features were extracted.

To extract 25 histogram group features in gray, LBP and LSP matrices, and 256 gray values were grouped

into the 25 histogram bands. Then the number of pixels in each band was counted. In LSN matrix number of pixels was counted to produce nine histogram features, as it can have only 9 values (0-8).

Table I. Features extracted from Gray, LSP, LSN and LBP Matrices

Features	Equation
Mean	$\mu = \sum_i p(i)$
Standard Deviation	$\sigma = \sqrt{\sum_i (i-\mu)^2 p(i)}$
Third Moment	$\sum_i (i-\mu)^3 p(i)$
Smoothness	$1 - {}^{1}/_{(1+\sigma^2)}$
Entropy	$-\sum_i p(i) log\{p(i)\}$
Uniformity	$\sum_{i,j} p(i,j)^2$
Gray level range	$max\{i \mid p(i) \neq 0\} - min\{i \mid p(i) \neq 0\}$

Table II. Features extracted from GLCM Matrix

Feature name	Equation
Mean	$\mu = \sum_{i,j} p(i,j)$
Variance	$\sigma^2 = \sqrt{\sum_{i,j} (i-\mu)^2 p(i,j)}$
Entropy	$-\sum_{i,j} p(i,j) log\{p(i,j)\}$
Uniformity	$\sum_i p(i)^2$
Homogeneity	$\sum_{i,j} p(i,j) / \{1+(i-j)^2\}$
Inertia	$\sum_{i,j} (i-j)^2 p(i,j)$
Cluster shade	$\sum_{i,j} (i+j-2\mu)^3 p(i,j)$
Cluster prominence	$\sum_{i,j} (i+j-2\mu)^4 p(i,j)$
Maximum probability	$max\{p(i,j)\}$
Correlation	$\sum_{i,j} (i-\mu)(j-\mu) / \sigma^2 p(i,j)$

Table III. Features extracted from GLRM

Feature	Equation
Short run	$\sum_{i,j} \{q(i,j)/j^2\} / R$
Long run	$\sum_{i,j} \{j^2 q(i,j)\} / R$
Gray level non-uniformity	$\sum_i (\sum_j q(i,j))^2 / R$
Run length non-uniformity	$\sum_j (\sum_i q(i,j))^2 / R$
Run ratio	$\sum_{i,j} R / jq(i,j)$
Entropy	$-\sum_{i,j} [q(i,j) log\{q(i,j)/R\}] / R$
Low gray level run	$\sum_{i,j} q(i,j) / Ri^2$
High gray level run	$\sum_{i,j} i^2 q(i,j) / R$
Short run low gray level	$\sum_{i,j} q(i,j) / Ri^2 j^2$
Short run high gray level	$\sum_{i,j} i^2 q(i,j) / R j^2$
Long run low gray level	$\sum_{i,j} j^2 q(i,j) / R i^2$
Long run high gray level	$\sum_{i,j} i^2 j^2 q(i,j) / R$

IV. RESULTS AND DISCUSSIONS

We were calculated 131 textural features of each bulk wheat seed images of four varieties as mentioned in previous sections. We used stepwise discrimination techniques to make six textural feature groups. Overall 58 textural features were taken while classifying the varieties. 9 textural features of gray level, 7 textural features of GLCM, 10 textural features of GLRM, 10 textural features of LBP, 10 textural features of LSP and 10 textural features of LSN textural groups were considered for classification using ANN (artificial neural network).It was observed in this study that as we were increased number of images to train using ANN (artificial neural network) we got better classification results. Average results accuracy is 76%.But as we increased the numbers of training images it took more time for training calculations. This affects on overall performance of classifier.

Table IV. Following table includes 9 textural features of gray, 7 textural features of GLCM, 10 textural features of GLRM, 10 textural features of LBP, 10

textural features of LSP, 10 textural features of LSN. In total 58 numbers of selected textural features.

GRAY	GLCM	GLRM	LBP	LSP	LSN
*HG9	Mean	Long run high gray level	HG25	HG15	HG6
HG17	Homogeneity	Run length non- uniformity	HG20	STD	HG5
HG16	Uniformity	Run ratio	HG13	HG22	HG4
HG2	Inertia	Short run high gray level	STD	HG20	Mean
Uniformity	Cluster shade	Entropy	HG1	HG14	Uniformity
Third moment	Variance	Gray level non- uniformity	HG21	Third moment	HG3
Entropy	Maximum probability	Long run	HG23	HG21	HG1
*STD	Entropy	High gray level run	Mean	HG24	STD
HG1		Short run	entropy	Uniformity	Third Moment
HG5		Long run low gray level	Uniformity	HG1	Entropy

*HG-Histogram group
**STD-Standard deviation

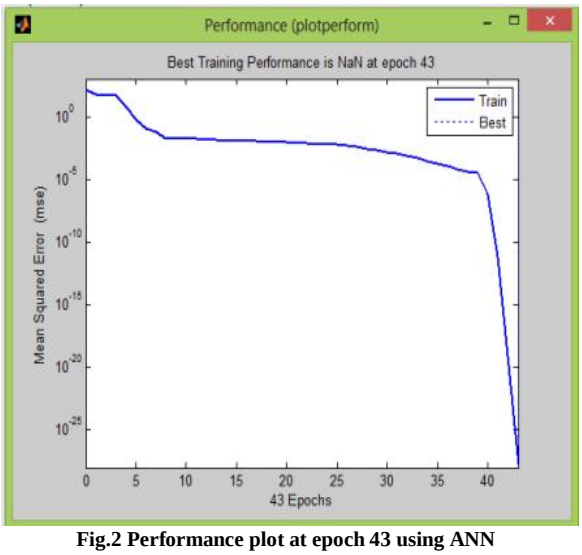

Fig.2 Performance plot at epoch 43 using ANN

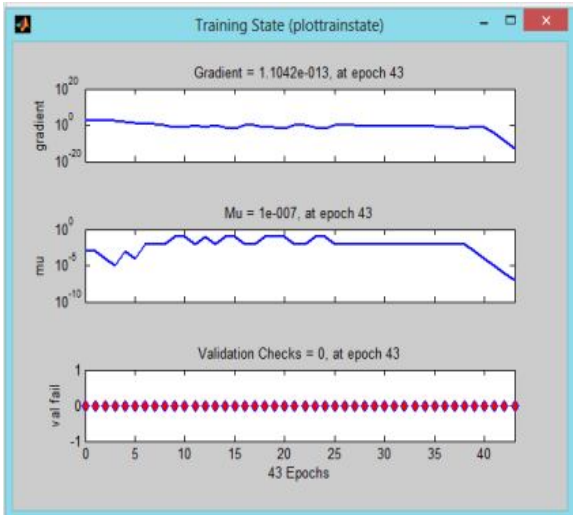

Fig.3 Training state graphs for 43 epoch using ANN

CONCLUSION

In this study in order to classify four wheat seed varieties i.e. Lokvan Gujrat, Lokvan MP, MP sure and Khapli, six number of textural feature groups were evaluated. Different varieties of wheat seeds usually create different textures in their bulk images because of their different shapes and colors. After the analysis of results this study indicated that the extracted textural features are good descriptors in identification of wheat seed varieties. We achieved an average accuracy 76% for the classification of four Indian wheat seed varieties results using ANN (artificial neural network) classifier. When increased the training dataset i.e. trained more number of images of each varieties, we got increment in classification results. Thus, it was discovered that for ANN based classification we need more number of data which is to be trained in order to improve its performance. But while using extent dataset for training it went to a problem of lengthy calculations and time constraints. This is the limitation of ANN classifier we observed in this study.

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