Development of an Automated Grading System of White Pea Bean Using Image Processing Techniques Convergence with Ann

Mesfin Fekadu Abeza, Sudhir Kumar Mohapatra, Befekadu Belete

Abstract*: White pea bean is a very important crop where its circulation in the market has to conform to the rules of quality inspection. Currently, white pea bean sample quality inspection is performed manually by human experts through visual evaluation and the constituents classified into foreign matter, rotten and diseased, healthy, broken, discolored, shriveled and pest damaged kernels. However, visual evaluation requires significant amount of time, trained and experienced people. Besides, it is affected by bias and inconsistencies associated with human nature. Such approach will not be satisfactory for large scale inspection and grading unless fully automated. A total of 24 features (14 color, 8 shape and 2 size) have been identified to model white pea bean sample constituents. For classification of White pea bean samples, a feedforward artificial neural network classifier with backpropagation learning algorithm, 24 input and 7 output nodes, corresponding to the number of features and classes respectively has been designed. The network is trained and its performance is compared against other classifiers using empirically. For the purpose of training the classifier, a total of 602 kernels and foreign matters have been collected from Ethiopian Grain Trade Enterprise. The training data is randomly apportioned into training (70%) and testing (30%). The classifier achieved an overall classification accuracy of 96.8%. The success rates for detecting foreign, rotten and diseased, healthy, broken, discolored, shriveled and pest damaged kernels are 94.9%, 96.5%, 96.3%, 97%, 97.9%, 97%, and 97.6%, respectively.

***Keywords:* Artificial Neural Network, quality assessment, Reconstructed Image, Image segmentation, Digital Image Processing**

I. INTRODUCTION

Haricot bean is one of the most important grain legumes grown in the low lands of Ethiopia, particularly in the Rift Valley. In these areas, white pea beans are grown for export purposes as well as for domestic consumption. Haricot bean is also a principal food crop particularly in the southern and eastern parts of Ethiopia. Haricot beans has different varieties such as white, red and mixed colors. The ECX (Ethiopian Commodity Exchange) mostly exported white haricot beans because of need of the market and most profitable agricultural product from other varieties of haricot beans. White pea bean has become an important export item in the country's pulse exports. In 2005/06 for instance, Ethiopia exported about 62, 262 tons of haricot beans /mainly white pea beans/ valued at about 22 million USD or about 193.7 million ETB, with a unit value of export of 353 USD/mt. The value of export was destined mainly to various countries such as: Sudan, Yemen, South Africa, UAE, USA, UK, Italy, Germany, Belgium and the Netherlands [1].Accordingly, white pea beans produced has to go through the intensive care of Ethiopian Commodity Exchange (ECX) to certify that the supplied white pea bean has met the minimum requirement of national standard for domestic and international markets. ECX offers an integrated warehouse system from the receipt of white pea bean on the basis of industry accepted grades and standards for each traded white pea bean by type to the ultimate delivery. Coming white pea bean is placed in warehouses worked by ECX. There are few experts participating in grading of major agricultural products in ECX at Addis Ababa branch. This number of experts are insufficient as compared with the big task.The increased awareness and sophistication of consumers have created the expectation for improved quality in consumer food products. This in turn has increased the need for enhanced quality monitoring. Quality itself is defined as the sum of all those attributes which can lead to the production of products acceptable to the consumer when they are combined. Quality has been the subject of a large number of studies. The basis of quality assessment is often subjective with attributes such as appearance, smell, texture, and flavour, frequently examined by human inspectors. Consequently, Francis found that human perception could be easily fooled. Together with the high labour costs, inconsistency and variability associated with human inspection accentuates the need for objective measurements systems. Recently automatic inspection systems, mainly based on camera-computer technology have been investigated for the sensory analysis of agricultural and food products. This system known as computer vision has proven to be successful for objective measurement of various agricultural and food products [2].

II. RELATED WORK

Advances in hardware and software for digital image processing have motivated several studies on the development of systems, to evaluate the quality of diverse agricultural products. Different grain qualities and varieties of assessment have been reported in the literature that are working in digital image processing. They use grain texture, morphology and color features to achieve their goals. The majority of these studies are focused on the application of computer vision system to

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agricultural products quality inspection and grading. Computer vision based inspection and grading of apple, oranges, strawberries, nuts, tomato, mushrooms, wheat, corn and rice are examples. These research works use image analysis for automatic information acquisition on quality of grain samples. Generally, based on their objectives research works is aimed at assessing the quality of cereal grain sample and that aim at identification of cereal grain varieties. Under this related work we discuss works that are associated with cereal grain quality assessment in general and white pea beans sample quality assessment in specific and also explains how different our work is from the other related works.The work in [3] 23 morphological features were used for the discriminant analysis of different cereal grains using machine vision. Classification accuracies of 98, 91, 97, 100 and 91% were recorded for CWRS (Canada Western Red Spring) wheat, CWAD (Canada Western Amber Durum) wheat, barley, oats and rye, respectively. The relationship between color and texture features of wheat samples to scab infection rate was studied using a neural network method.The work in [4], China use an image analysis technique to identify rice seed varieties was developed recently. A neural network model was used for pattern classification. In recording the images, one rice seed image was taken at a time. In this work, color and morphological features were used as classification parameters. They used MATHLAB 6.5 programming language to extract color and morphological features of individual seeds. From color features of the mean and variance of RGB components were calculated. Six varieties (ey795, syz3, xs11, xy5968, xy9308, z903) rice seeds, which are widely planted in Zhejiang Province of china, were considered for the research work. The experimentation result indicated that the classification accuracies are 90.00%, 88.00%, 95.00%, 82.00%, 74.00%, 80.00% for ey7954, syz3, xs11, xy5968, xy9308, z903 respectively.

The main aim of the study in [5] is to elaborate complete methodology for the identification of varieties, the level of contamination and other visual features of malting barley with the use of computer science technologies, such as neural image analysis. The work classifies malting barley sample into three classes namely, Beatrix, Sebastian, and Xanadu. To do this, the work models barley using 46 different features composed of geometrical such as area, circumference etc. and non-geometrical such as color features. The work applied neural network for the classification of extracted features. The authors claimed that the optimum model for variety recognition is provided by the color features used to model barley. As a consequence, the work concluded that color features can alone be used to classify malting barley. However, the work does not mention the classification accuracy achieved.In [6], the development of a digital imaging system and ANN capable of measuring the geometric and shape related parameters for differentiating between rains fed wheat grain cultivars in order to distinguish them. This work used 6 color, 11 morphological and 4 shape features to model wheat. Like most other related works, this work used ANN to classify wheat into 6 cultivars, namely, Sardari, Sardari39, Zardak, Azar 2, ABR1, and Ohadi. The Authors claimed that 86.48% of classification accuracy was achieved.In [7], the ability of Multi-Layer Perceptron and Neuro-Fuzzy neural networks to classify corn seed varieties based on mixed morphological and color features has been evaluated. Average classification accuracy of corn seed varieties were obtained 94% and 96% by MLP and Neuro-Fuzzy classifiers respectively. However, the work dealt with healthy kernels only and do not address quality factors that describe damaged kernels such as discolored, PD, shriveled, RD and broken.The work in [8] emphases on the identification of corn kernel shape for the purpose of discriminating between whole and broken kernels of maize. This work, does not address quality factors of maize such as shriveled, discolored and PD. Moreover, the segmentation technique used is based on the green channel of the image. This was one of its shortcomings.The work in [9] modeled damaged, shriveled and foreign matters found in corn sample. According to the work, damaged kernels are those that are broken or discolored. However, according to ESA, each one of these is separate quality factors. Moreover, the work does not cover maize sample quality factors, namely, discolored, PD and RD kernels of maize. In short, this work does not detect discolored, PD or broken maize kernels. Instead, it simply addresses all these quality factors as damaged.The work in [10] is about corn kernel damage evaluation. The primary objective of this work was to develop a computer vision system to capture corn kernel images and to classify the images into categories of sound and damaged (germ-damaged and blue-eyed and mold-damaged). This work claimed that about 90% of all damaged corn kernels in the Midwestern U.S. corn market could be classified into either germ–damaged or blue– eye mold–damaged categories. However, the quality factors, namely, shriveled, broken, discolored and PD are not addressed by this work.The work in [11] is the classification of Ethiopian coffee based on region of growth. This work is based on healthy coffee aimed at discriminating different varieties of Ethiopian coffee using image processing technology. In this work, morphological and color features were extracted from coffee bean images that were taken from six regions of Ethiopia, namely, Bale, Harar, Jima, Limu, Sidamo and Welega. The work tested the classification accuracy of each selected feature set, using Naïve Bayes and neural network classifiers. The experiment was conducted under three scenarios of the features data set such as morphology, color and both morphology and color features.The work in [12] use a trial investigation of the use of computer vision in sorting fresh strawberries, based on size and shape, showed a result that the developed system was able to sort the 600 strawberries tested with an accuracy of 94-98% into three grades based on shape and five grades on size.

III. PROPOSED METHODOLOGY

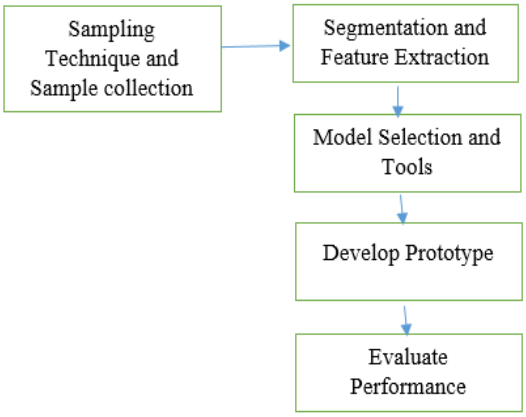

Fig.1. Design and Methodology

Sampling is one of the main procedures in white pea bean classification and quality assessment. In the current practice of the manual system, the sample drawer draws a 'representative' sample of 3kg per 10 tons of a truck, which is an average carrying capacity of a truck, on its arrival. From this 3kg, 125g is used for the analysis and the remaining was used for other references.

In this regard, we have taken 60 images in which the images contain 602 white pea bean kernels. From these samples, 70% were used for training and 30% were used for testing and validation purposes.

The samples of white pea beans were obtained from the warehouse of Ethiopian Commodity Exchange. A digital camera cannon Model SD630 with specification of 12.1 mega pixels, used to capture white pea bean kernel images.

This research involved the extraction of morphological and color features from digitized images of sampled white pea beans to generate a useful input database for quality value classification. Color features of the sample white pea beans were extracted from segmented white pea bean images. Morphological features were extracted from the binary images of the gray scale images of the original white pea bean color images.Developing the quality value classification demands suitable and applicable selection of models to run, compute and analyze the empirical dataset generated through image processing and analysis approaches. Artificial Neural Network, Naïve Baye's, and C4.5 classification model were employed to carry out the intended tasks of developing the quality value classifier. The Naive Bayes classifier is also found an important classification approach that requires a small amount of training data to estimate the parameters (means and variances of the variables) necessary for classification [13]. Neural networks are data driven self-adaptive methods in that they can adjust themselves to the data without any explicit specification of functional or distributional form for the underlying model. They are also recognized as universal functional approximates, in that the neural networks can provide a projection of any function with an arbitrary accuracy [14].

In addition, C4.5 classifiers was found to be important for the classification problem. It creates a decision tree based on the attribute values of the available training data in order to classify a new item, by identifying the attribute that discriminates the various instances most clearly. Possibility of higher information gain is raised as a consequence from the feature that tells most about the data instances. MATLAB version R2016b was used to implement the prototype of the system. Weka 3.6.4 was used to implement the Naïve Bayes and C4.5 classification model. A prototype has developed is done on the basis of agricultural procedure of Ethiopia Commodity Exchange standards. According to the standard, white pea beans are divided into five classes.

Each model was evaluated by running a test dataset on the classifier built using the training dataset. The model performance of the classifiers was returned as an output that contains performance matrices and percentage accuracy measures for each class, further summarized into a confusion matrix. Confusion matrix is a kind of a contingency table, used to drive true positives, true negatives, false positives and false negatives indicating the correct/incorrect allotment of samples into their respective classes.

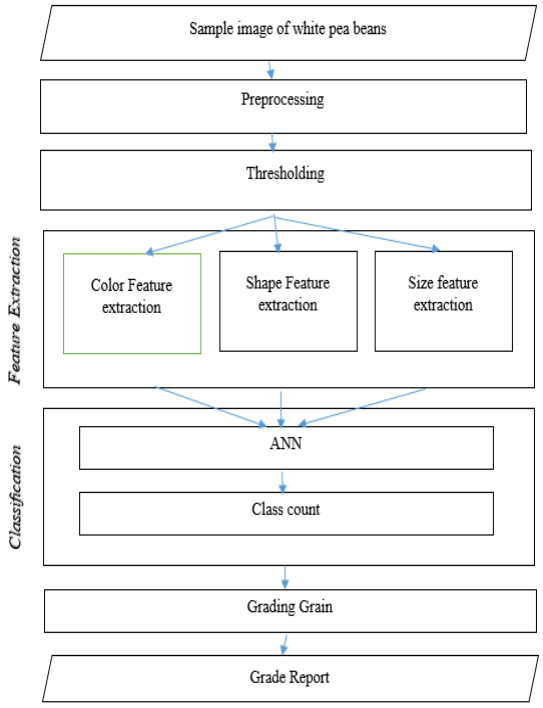

Fig.2. System Architecture

Preprocessing component performs the job of preprocessing the input image. The component does the preliminary task of making the input image ready for the segmentation component. Due to lack of smoothness of the background of the images taken, in a segmented image there could be some groups of pixels having the foreground grey level value while being enclosed in the background. Naturally, these regions belong to the background but they appear as foreground objects. In this work, we call these as false regions. False regions are removed in this component.

The segmentation component of our proposed architecture is responsible for carrying out the work of separating white pea bean sample constituents from each other and from the background of the image. This component contains thresholding and the thresholding sub-component extracts information from each of the three binary images to form an intermediate image called reconstructed image. The final job of the segmentation component is carried out by the merger sub-component.

Feature extraction component is responsible for extracting the descriptive features of the white pea bean sample constituents. This component contains the color features extraction, the shape features extraction and the size features extraction sub-components. The features extracted from white pea bean images can be grouped into three categories, namely, color, size, and shape. To describe white pea bean sample constituents, we identified 14 color features, 2 size features, and 8 shape features.

Classification component contains ANN classifier and the class count sub-components. The ANN classifies white pea bean sample into seven classes. The class count sub-component is responsible for counting the number of sample constituents belonging to each class. Although there are other methods like mathematical functions, rule-based algorithm or statistical methods available for classification, we chose ANNs over others. There are several reasons for

choosing neural networks over other methods for the purpose of this research work. The classification of grain kernels cannot be easy using unique mathematical functions. This is due to the variation in morphology, color and texture of the grain kernels under consideration. ANNs have the potential of solving problems in which some inputs and corresponding output values are known, but the relationship between the inputs and outputs is difficult to translate into a mathematical function. When compared to other methods, ANNs can tolerate noise better and exhibit low classification error rates. Moreover, compared to statistical methods, ANNs using the BP network could be easily modified to accommodate more features. To add empirical experience to the above claims, we trained naïve Bayesian classifier and ANN classifier on the same training data set. We compared their performance based on classification accuracy and we found out that ANN performs better than the naïve Bayesian classifier. The neural network architecture in this work is a three-layered F-F network with sigmoid hidden and softmax output neurons. Such network can classify vectors arbitrarily well, given enough neurons in its hidden layer. The input layer contains 24 neurons corresponding to each 24 inputs and the output layer consists of 7 neurons corresponding to each 7 output classes. Softmax is a neural transfer function. Transfer functions calculate a layer's output from its net input. The network is designed to have only one hidden layer consisting of 45 nodes. The hidden layer of the neural network is composed of 45 neurons. This number of neurons in the hidden layer is selected empirically based on the performance it exhibited over smaller and larger number of neurons. Moreover, the decision to use only 1 hidden layer is made based on facts found in the literature. There is no reason to use any more than one hidden layer.

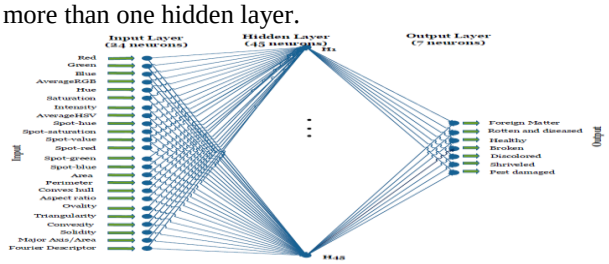

Fig.3. Design of ANN Used for the Classification of white pea bean Sample

The network is designed to use B-P algorithm training. To measure the performance of the network during training phase, we preferred to use cross-entropy error function over mean square error (MSE). Compared to MSE, cross entropy function is proven to accelerate the backpropagation algorithm and to provide good overall network performance.

IV. EXPERIMENTAL RESULTS

A total of 602 of White pea bean kernels and foreign matter are prepared to train, validate and test the proposed model. These 602 White pea bean sample constituents are separated into their corresponding 7 classes based on their characteristics. Therefore, we finally have 7 outputs each corresponding to each of the 7 classes. The data were partitioned randomly into training, validation and test sets. Image acquisition is done using cannon Model SD630 with specification of 12.1 mega pixels. The images taken are all 24-bit color JPEG format. The number of White pea bean kernels per image is different for the different classes as shown in Table-I.

During image acquisition, the camera is mounted on a stand which provides easy vertical movement. The distance between the camera and the sample was fixed at 14 cm to maintain the same vertical distance on each image taken. During background color selection, we compared a red, blue black, and light blue colors. We observed that the light blue color makes a good contrast with the foreground objects and achieved better segmentation result. Consequently, for each image, a blue background is used. The samples of White pea bean are placed directly under the camera for image acquisition.

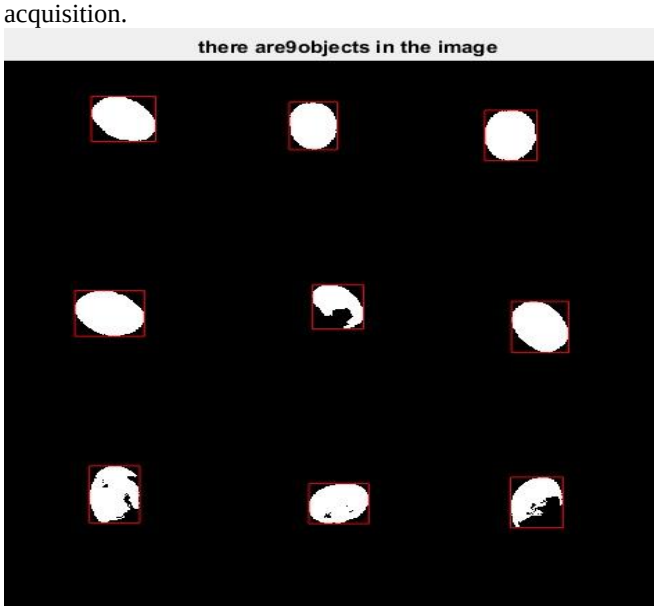

Fig.4. Object of Interest

For neural network training, 70% of the data is used. The rest of the data is used for validation and testing each consisting of 15% of the input data. The training set is presented to the network during training. The training set is used to fine tune the weights of the network. Whereas, the validation set are used to measure network's generalization ability, and to halt training when generalization stops improving. The testing data have no effect on training and so provide an independent measure of network performance during and after training. Similarly, for naïve Bayesian classification, 70% of the data is used for training and the rest 30% is used for testing.

As this is supervised effort, the training data needs to be labeled. The labels are presented to the neural network as binary code. Since there are 7 classes into which the White pea bean sample constituents are to be classified, the corresponding number of bits in the binary code is also set to seven. These classes and the number of images used for each in the training process are shown in Table-I.

Table-I: Data set description

Model (% correctly classified)	Morphology Feature	Color Feature	Combined Feature Performance
C 4.5	73.91%	64.27%	82.09%
ANN	82.8%	75.6%	96.8%
Naïve Bayes	74.01%	66.79%	76.79

Test Results

Tests are conducted on naïve Bayesian, and ANN classifiers to determine the best performing classifier based on the criterion of classification accuracy.

NAÏVE BAYESIAN CLASSIFIER TEST RESULTS

The performance of the naïve Bayesian classifier was tested with 181(30% of the training data) data items. The test confusion matrix of the trained naïve Bayesian classifier is depicted in Table 5.2. The diagonal elements show instances that were correctly classified. For this classifier, the classification accuracy of RD, shriveled, broken, discolored, healthy, foreign, and PD are 54.1%, 100%, 93.5%, 100%, 51.5%, 100%, and 58.6% respectively. The overall classification accuracy obtained is 76.79%. This is calculated by summing the number of correctly classified kernels in each class and dividing the result by the total number of test data (181). The classification accuracy for the classes RD, healthy, and PD is below 70%. This has affected the overall performance of the naïve Bayesian classifier to significantly underperform, compared to the neural network classifier.

ANN Classifier Test Results

After the data was partitioned the neural network is trained. The whole process, i.e., training, validation and testing took only 2 seconds. During training, cross-entropy was used as the error function. The neural network training 80 process is halted at the 62th iteration (epoch) at which the validation error started to rise and the training error was dropping. This training process is shown Figure 5.1.

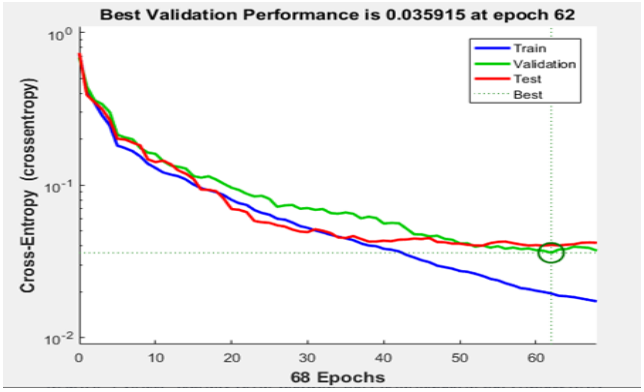

Fig.4. Cross_ entropy Error Showing the Performance of the Trained ANN

Accordingly, classification accuracies of 96.7%, 97.8%, and 96.7% have been achieved for training, validation and testing respectively. Moreover, an overall classification accuracy of

Table-II: Performance of model in different classifiers

Target Class Description	Binary Code (Class labels)	Number of Kernels
Foreign matter	0000001	59
RD	0000010	89
Healthy	0000100	157
Broken	0001000	35
Discolored	0010000	142
Shriveled	0100000	34
PD	1000000	86
Total		**602**

96.8% is achieved. This accuracy is calculated by dividing the total number of correctly classified kernels by 602 (by the total number of kernels in the sample). Since the naïve Bayesian classifier resulted in 76.79% of classification accuracy and the ANN achieved 96.8% for the same, we conclude that ANN out performs naïve Bayesian classifier.

Scenario One

PD (Pest damaged), discolored, and RD (rotten and diseased) areas in kernels are modeled using the area occupied by the damage and the corresponding hue, saturation, value (intensity), red, green and blue color values of the areas. In this work, the hue, saturation, value, red, green and blue values that are associated with damaged areas within a kernel are termed as spot-hue, spot-saturation, spot-value, spot-red, spot-green and spot-blue. In this scenario the effectiveness of the features spot- hue, spot-saturation, spot-value, spot-red, spot-green and spot-blue attributes are studied. Accordingly, we retrained the classifier without the inclusion of these attribute in the training data. As a result, we observed that the discriminative power of spot-hue, spot-saturation and spot-value, spot-red, spot-green and spot-blue attributes are so high that without these features, the classification accuracy of the ANN classifier drops significantly. The overall classification accuracy of the ANN classifier dropped to 82.8%.

Scenario Two

In this scenario, the discriminative power of the size feature is examined. We experimented to see the effect of area by training the neural network excluding area attribute from the feature data set and training the neural network. Originally, we incorporated area as a feature to model the size of White pea bean kernels with the intention to discriminate between shriveled and other kernels. Therefore, in this scenario, we expected shriveled kernels to be misclassified into other classes. However, the accuracy of the classifier was observed to reduce from 96.8% to 94.4%.

Scenario Three

In this scenario we examined the discriminative power of shape features. In light of this, we trained an ANN without the inclusion of these features in the training data set. We found out that the overall classification accuracy of the classifier was reduced from 96.8% to 93.4%.

Scenario Four

In this scenario, the discriminative power of color features is examined. This is done by training the ANN without the inclusion of color features in the

training set. In doing so, we found out that the ANN classification accuracy dropped from 96.8% to 65.5%.

Comparison with Manual work

Finally, the system's performance is compared against the manual counterpart based on the time taken and efficiency to do the same job by an expert from the EGTE. The expert has taken 4 to 8 minutes to identify and count foreign, rotten and diseased, healthy, broken, discolored, shriveled and pest damaged kernels from a mixture. However, our proposed system completed the job within 45 seconds.

V. CONCLUTIONS

White pea bean is used as a major food item around the world and especially in sub-Saharan Africa. Countries, including Ethiopia, produce White pea bean both for domestic and export consumptions. In industrialized countries, White pea bean is largely used as livestock feed and as a raw material for industrial products. Besides, White pea bean is used as input to factories that produce processed food products. White pea bean grains may be damaged during harvesting, storing, and transportation. Some of the damage types merely reduce the quality of the grain while others make it unsafe to eat. Because of this, governments impose a standard on White pea bean destined either to the inland or overseas market to assure its quality. These standard sets criteria by which White pea bean quality is evaluated. The standard is based on morphological and chemical characteristics of White pea bean. Currently, there is no automated technique that can assess White pea bean quality. Rather, White pea bean quality is assessed manually. However, manual evaluation takes significant amount of time and requires trained and experienced people. This is especially evident during large scale inspection. Naturally, this manual process of quality assessment is prone to bias and inconsistencies. In order to eliminate most of the shortcomings of the manual work, it is important to employ automated quality assessment system. Automated White pea bean quality assessment has many important advantages over the manual technique. The major advantage of automated White pea bean quality assessment is its objective nature. This helps to describe visible attributes accurately, without bias and inconsistencies. Compared to the manual counterpart, automated systems take lesser time and effort. Therefore, in this research work, automatic White pea bean quality assessment system is developed to classify White pea bean sample consistently and objectively. For this, best segmentation algorithm is developed to identify the damaged areas of White pea bean kernels. A total of 24 features are identified to model the constituents of White pea bean sample. Moreover, system architecture is designed that works based on the proposed segmentation algorithm. For classification purpose, a feedforward artificial neural network with 24 input nodes and 7 output nodes and backpropagation algorithm, corresponding to the number of input features and output classes respectively is designed. The network's performance is compared against other existing classifiers both empirically and based on supporting facts from the literature.Results show that the overall success rate for the classification of White pea bean sample is 96.8%. The success rates for detecting foreign, rotten and diseased, healthy, broken, discolored, shriveled and pest damaged kernels are 94.9%, 96.5%, 96.3%, 97%, 97.9%, 97%, and 97.6%, respectively. Moreover, these results show that, the proposed segmentation algorithm and system architecture are effective in assessing the quality of White pea bean sample constituents according to the standard set for White pea bean sample by ESA. Hence, it is feasible to assess the quality of White pea bean sample using digital image processing and ANN. Therefore, it is practically possible to void the negative aspects of the manual work.

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