Detection of Impurities in Wheat and Classification of Durum Wheat Vitreousness in a Dynamic System

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***Abstract*— One of the main food supplies for the survival of humankind is wheat so, a favourable quality processing of wheat is essential. After harvesting, it goes through many procedures from its separation from chaff to its packaging. Nowadays, many of these procedures are conducted with automatic systems due to the development in computer sciences which leads to decreasing cost of labour and time and increasing food quality. One of the main concerns of quality food production is to provide a customer with the product in its purest form which means the product must be separated from all foreign matters. The vitreousness of durum wheat is also a measure of quality. If the wheat is vitreous, it means that the wheat is of good quality. If not, then it is of poor quality. In this study, type-1252 durum wheat seeds have been separated from junk using 10 morphological properties of wheat seeds and the vitreousness of wheat is determined through 45 colour features through the uncompressed video image taken with the camera Prosilica GT2000c. With the purpose of obtaining high quality vitreous durum wheat storage with no junk, this article has adopted various image processing techniques from image pre-processing to feature extraction and realized the classification process with Artificial Neural Network(ANN). The image processing has been realized in a computer environment and the results show that the image processing is successful and the determination of vitreous durum wheat seeds and the detection of wheat seeds from junk was accurate.**

***Keywords*— ANN, Blob Analysis, Colour Features, Feature Extraction, Image Processing, Junk, Morphological Properties, Segmentation, Vitreousness, Wheat Seed**

I. INTRODUCTION

Wheat, which is the main ingredient of amylaceous products such as bread and pasta, is also one of the most necessary materials for human beings to survive. Furthermore, a product's quality measure is important in industry for commercial reasons. After the process of harvesting, many procedures are applied to wheat seeds such as the separation of wheat from chaff and the packaging process. Following these processes, they are stored in warehouses to be sold at specified intervals [1]. A series of instrumental and chemical analysis can be used manually to inspect or classify wheat seeds. The disadvantages of these manual inspection and classification methods are that they are subjective, time consuming, less efficient, costly and it is also virtually impossible to obtain safe wheat grains without damaging its structure [2, 3].

In recent years, automatic systems have been used for the safe inspection and the classification of wheat seeds to counteract the disadvantages of manual processes. Due to the developments in computer technologies, wheat inspection and classification using machine vision systems and image processing techniques have become an extensive area for researchers. The features that make these methods popular are that they are able to visually characterize wheat grains according to their physical, textural and colour attributes. Moreover, they are objective, speedy, most efficient, cheap, repeatable, and harmless to wheat grains [2, 3].

Through the last years, machine vision and image processing techniques have been used by many researchers for their evaluation such that if they really meet the expectations for the inspection and classification of the quality of wheat. There have been many studies about the determination of the properties of single type wheat seed, separation of one type wheat from another or identification of damaged wheat seeds, and quality measurement of wheat seeds based on their vitreousness but there have not been many researches about separating the wheat seeds from non-wheat seeds [1]. In a study conducted by Pourreza et al., nine different wheat classes growing in Iran have been classified according to their textural properties extracted from Gray Level, GLCM (Gray Level Co-occurrence Matrix), GLRM (Gray Level Run-length Matrix), LBP (Local Binary Pattern), LSP (Local Similarity Pattern) and LSN (Local Similarity Numbers) matrices and classified using LDA (Linear Discriminate Analysis [4]. Xia et al. classified a single type wheat with regards to its quality by accounting its 7 morphological properties and 6 colour properties using RGB and HIS colour models [3]. In an article written by Güneş et al., it is explained the varieties of wheat growing in Turkey are classified according to its textural analysis using GLCM and LBP methods and k-Nearest Neighbour type classifier [5]. In a study conducted by Babalik et al., variety of wheat classes are identified with 9 morphological and 3 colour features based and RGB colour space using M-SVM (Multiclass Support Vector Machines) and BPSO (Binary Particle Swarm Optimization algorithm [6]. In another study, Farahani tried to determine the best potential morphologic features to classify 5 different types of durum wheat [7]. Manickavasagan et al. tried to measure the ability of a machine vision system with a monochrome camera to classify the different types of western Canadian wheat types by using bulk sample analysis [8]. Williams et al. have evaluated two different digital image analysis (DIA) approaches to quantifying wheat seed shape for exploring trait correlations and QTL (Quantitative Trait Loci) mapping [9]. In a study conducted by Wiwart et al. wheat and spelts varieties are identified based on 9 physical features and 12 color features and determination of the most effective feature in the classification is done by using Principal Component Analysis (PCA) [10]. In 1999, Luo et al. identified damaged wheat kernels using a non-parametric classifier and obtained the possible best results using 24 colour and 4 morphological properties after the feature elimination process [11]. Choudhary et al. conducted a study on the classification of different type Canadian wheats with linear and quadratic statistical classifiers according to 51 morphological, 93 colour, 56 textuaral and 135 wavelet features extracted from the images acquired using an area scan camera [12]. All these studies generally have been made with the purpose of classifying different types of wheat. However, there is also a small number of studies about purification of wheat from its chaff and other impurities. One of these studies is made by Ebrahimi et al. to propose a machine vision automatic grading system which separates the wheat from the impurities within [1]. The objective of another study conducted by Paliwal et al. is to develop an algorithm which classifies 5 different types of Canadian wheats and also differentiates the wheats from non-wheat materials [13]. In another study, FN Chen et al. have developed an image processing algorithm which determines black germ wheat [14].In another study realized by Seranti et al., vitreous, yellow berry and Fusarium damaged wheat kernels are investigated on a conveyor belt using hyperspectral imaging techniques and the success rates were high but the sample images shows that the system is not fully automated [15]. It can be seen from these examples that so few of the studies are about purification of wheat from non-wheat materials and quality classification of one type wheat based on its vitreousness. Also, all of these studies are conducted in stationary environment and the possible outcomes are not known for a non-stationary environment [16].

In this study, our objective is to obtain good quality type-1252 durum wheat grains by visually separating the impurities from wheat grains and classifying the wheat grains among themselves according to them being vitreous or non-vitreous grains in a dynamic system using image processing techniques and Artificial Neural Network (ANN). The process stages that is used in this study are shown in Fig.1.

II. Material and Methods

A. *Image Acquisition*

The system used consists of a conveyor belt system where the durum wheat grains are moving upon, image acquisition camera Prosilica GT2000C, and illumination apparatus with a shady box stand for preventing the shadow formation on the background.

Prosilica GT2000C camera, which is used for the study, is a 2.2 megapixel, RGB camera with 2048 x 1088 resolution, CMOS type sensor, 53.7fps maximum frame rate at full resolution and efficient operation temperature range between -20 °C and +65 ° [17]. The camera has been placed atop the illumination apparatus and daylight coloured powerleds have been placed around the camera. Under the illumination apparatus there is a ground glass around the camera lens so that the light can refract uniformly. The camera and the light illumination apparatus has been placed above a shady box so that the outside light does not affect the wheat grains and shadow formation can be prevented.

The camera views a 8 cm x 10 cm area inside the box and a 7 sec uncompressed video obtained from the camera is transmitted to the image processing computer software with an ethernet cable. Then, the video extracted to its frames and the resulting 65 frames are processed in this study. Each image sample has the size of 1088 x 893 pixels. The system used for this study is shown in Fig.2. Also, a frame sample of the video acquired is shown in Fig. 3.

B. *Image Preprocessing and Segmentation*

In the first phase of the work, frames of the video of which the wheats and non-wheat materials reside on a moving conveyor belt are obtained for the image processing and all the frames have been subjected to same processes in a loop [16]. First, the colormap of the images adjusted suitably after several trials so that the image segmentation is successful. The image with adjusted colormap is shown in Fig.4.

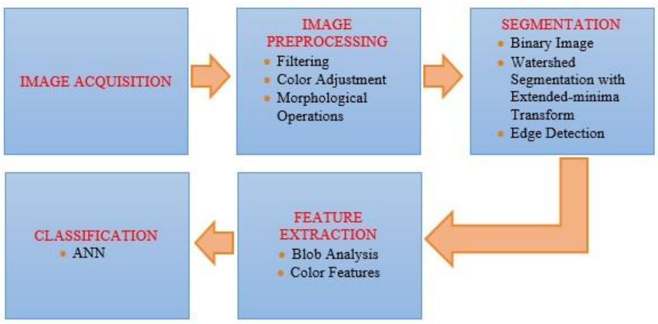

Fig. 1 Process stages that were followed in the study

Fig. 2 Dynamic system used for acquiring video sample of durum wheat grains with impurities

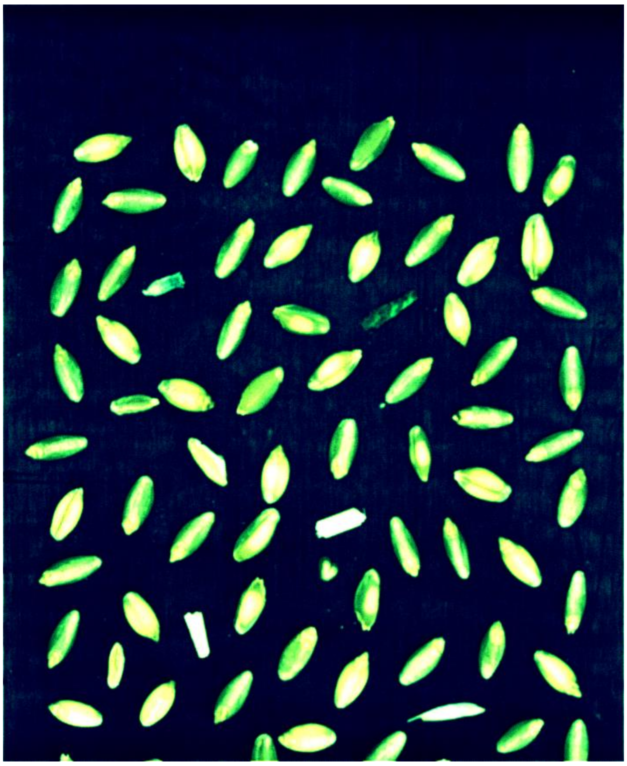

Fig. 4 The frame sample of the video with adjusted colormap

Fig. 3 Frame sample of the video visualizing durum wheat grains with impurities

After adjusting the colormap, the images are turned into gray images and the objects touching to the image borders are removed so all the processes can be applied to full objects. Next, the images are subjected to a 5 x 5 median filter which is a non-linear filter offering an effective noise reduction without blurring the image [3]. After the filtering process, the background is subtracted from the image with "top-hat" operation so the background noise does not affect the image segmentation [16]. The median filtered image with background subtraction is shown in Fig. 5. Then, morphologically "open" and "close" operations have been applied to the images for smoothing the boundaries of the objects and contrast values of the images have been adjusted for reducing the edge detection errors [16]. The final state of the frame sample after going through several morphological operations is shown in Fig.6. Lastly, they were converted to binary images using an appropriate threshold value. The binary image of the frame sample is shown in Fig.7.

Durum wheat grains and other non-wheat materials reside on the conveyor belt in a random order so the grains are closer to other materials or touch other grains or the other non-wheat materials. The morphological operation "erode" can shrink the objects, thus can separate the touching objects. However, the objects can still be connected despite the touching area is really small and too much "erode" operation can cause a distortion on the physical features [16]. In such conditions, a watershed algorithm which is a segmentation algorithm that can divide the image into multiple regions where the darker colours represent a region with lower altitude and lighter colours represent a region with higher altitude topologically [18]. The first step to apply watershed transform efficiently for segmentation is the application of distance transform which labels each existing pixel according to the distance with the nearest boundary pixel in a binary image [18]. Despite the fact that the distance transform is successful for segmenting round and simple touching objects, it is not efficient for kernels with irregular shapes [18]. The reason why it is not successful to segment kernels with irregular shapes is due to large clusters of objects which causes over-segmentation leads to large number of local minima occurrence [19]. So, in our study, we used a watershed segmentation algorithm with extended-minima transform to segment the durum wheat grains. Thus, the extended-minima transform produces markers for objects where local minima with greater depth than *h* representing a depth value specified by the user of the algorithm are marked and where local minima with less depth than *h* are eliminated. By using minima imposition technique, the creation of minima at the specific locations associated with the markers is realized [19]. After this procedure, watershed segmentation is applied which results in perfect segmentation for touching grains. Two wheat grains before and after watershed segmentation process is shown in Fig.8. The boundaries of objects found using edge detection algorithm is shown in Fig.9.

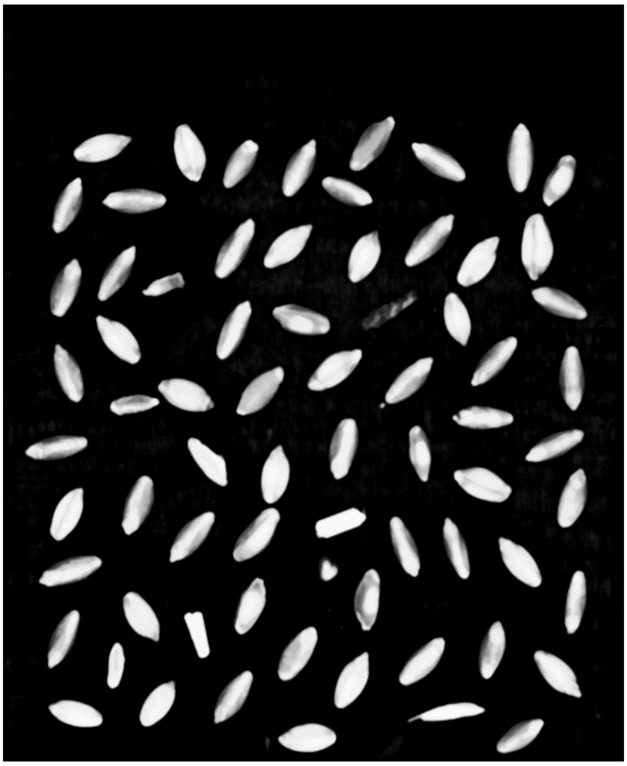

Fig. 5 Median filtered image with background subtraction

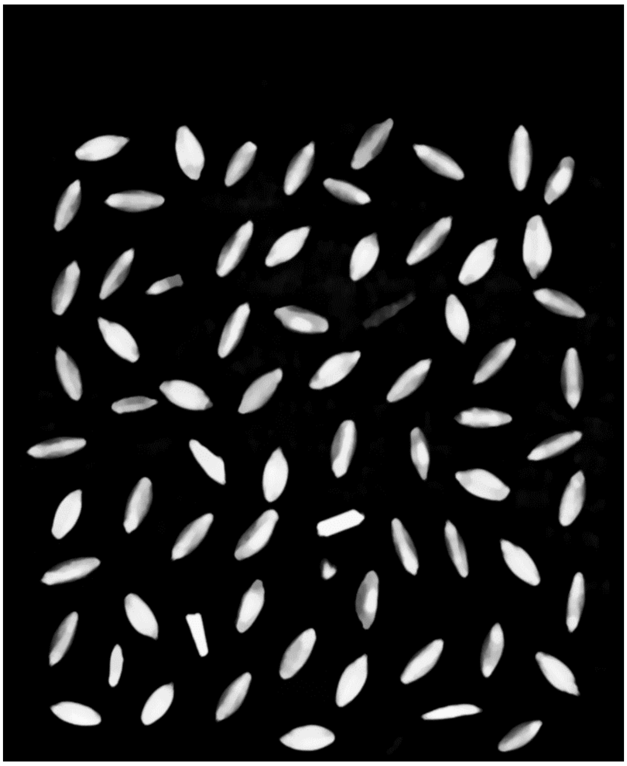

Fig. 6 Frame sample after several morphological operations

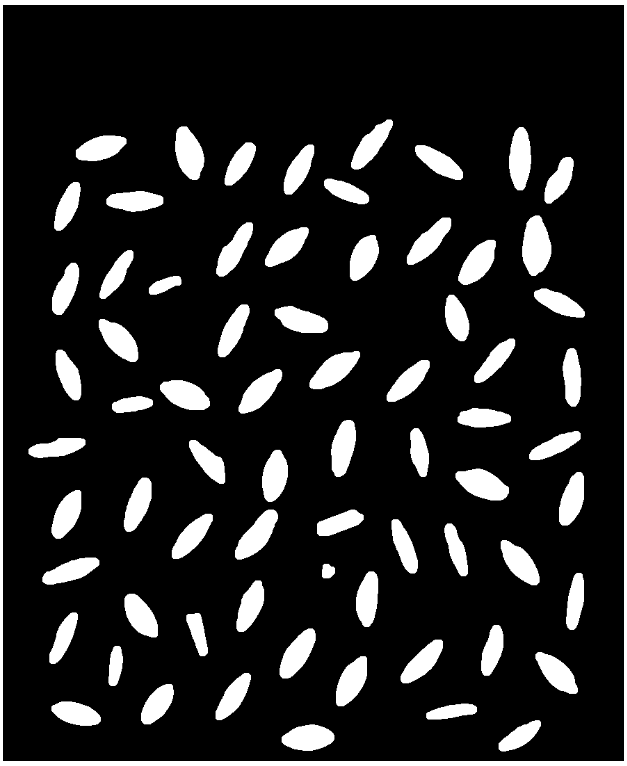

Fig. 7 Binary image of the frame sample

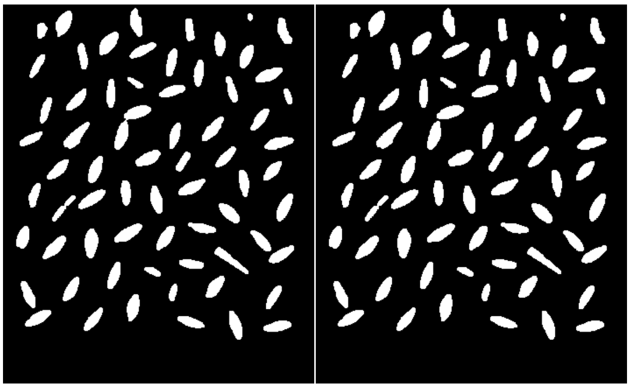

Fig. 8 Frame samples before and after watershed segmentation with local-minima transform

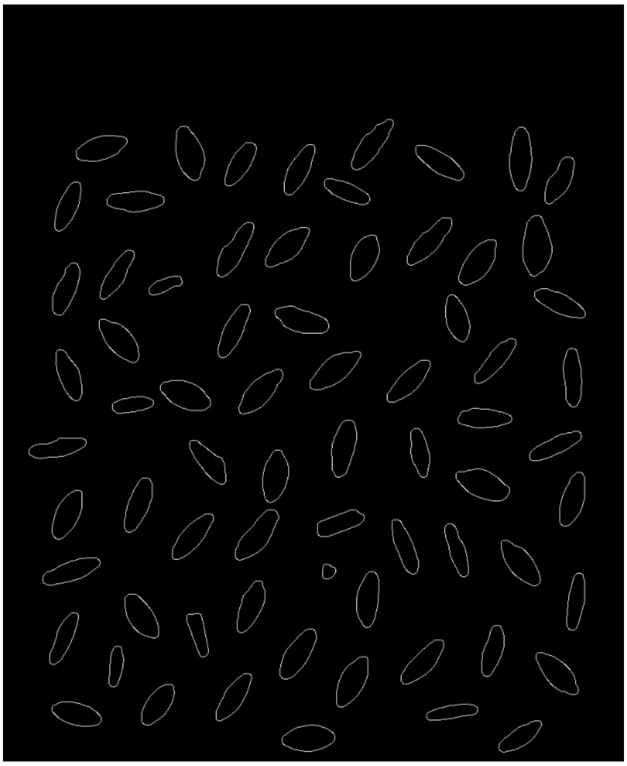

Fig. 9 The edge detected binary image of the frame sample

C. *Feature Extraction*

The blob is the region of connected pixels of an object and blob analysis is the method, which has been used in the study for feature extraction process, investigates blob regions and provides us the information about the morphological properties of regions [20]. The pixels are distinguished from each other based on their values and are labelled into 2 categories with blob analysis algorithm [20]. The foreground category is generally the pixels with a non-zero value and the other category is the background where the pixels with a zero value belong [20]. Thus, the blob analysis algorithm extracts the morphological properties of the object regions in the images.

In the study, blob analysis algorithm has been used for the feature extraction process to measure the properties of wheat grain regions after the segmentation process and 10 morphological features are extracted for the classification of vitreous and non-vitreous wheat grains and the elimination of the impurities in the wheat grains. 6 morphological features used in this study which are area, major axis, minor axis, perimeter, equivalent diameter, eccentricity are extracted directly by blob analysis. The other 4 features which are roundness, shape factor, compactness and extent are derived from the properties found by blob analysis [6].

TABLE I
FEATURES USED AND THEIR DEFINITIONS

FEATURES	DEFINITION
Area	Number of pixels in the region
Major Axis	The length(in pixels) of the major axis of the ellipse
Minor Axis	The length(in pixels) of the minor axis of the ellipse
Perimeter	The length(in pixels) around the boundary of the region
Equivalent Diameter	The diameter of a circle with the same area as the region
Eccentricity	The ratio of the distance between the foci of the ellipse and its major axis length
Roundness	4.Area/π(Major Axis)2
Shape Factor	$4.\pi.\text{Area}/\text{Perimeter}^2$
Compactness	Sqrt(4.Area/π)/Major Axis
Extent	The ratio of pixels in the region to pixels in the total bounding box
R, G, B	Red, Green, Blue
Y, Cb, Cr	Luminance, Blue Difference Chroma, Red Difference Chroma
H, S, V	Hue, Saturation, Value
X, Y, Z	Red Component, Luminance(Lightness), Blue Component
L, a*, b*	Non-linear transformation of X, Y, Z

After the extraction of morphological properties, colour features are extracted which are more prominent than morphological features for the determination of vitreousness. One of the colour features extracted for this study are R, G and B mean intensities of RGB colour space which is the most popular hardware-oriented color space [21]. Hardware-oriented colour spaces are used for hardware processing, such as image acquisition, storage and display and they can distinguish small amount of change in colour [21]. Another colour space used in this study YCbCr and all the mean intensities of Y, Cb and Cr for all objects have been calculated and used as features. Also, human-oriented colour spaces which correspond to human perceptions such as tint, shade and tone have been used in this study and HSV human-oriented colour space has been used in this study. Besides hardware and human-oriented colour spaces, CIELAB and CIEXYZ instrumental color spaces standardized by the Commission Internationale d'Eclairage (CIE) have been used as well. For all objects H, S, V, L, a*, b*, X, Y, Z mean intensities have been found to use as colour features. The features used for this study and their definitions are shown in the Table I [6, 7, 21, 22, 23].

D. *Artificial Neural Network*

Artificial Neural Networks (ANN) have been developed for the modelling and solving complex problems in the real world by imitating the functions of human brain [1]. A typical network made up of three sequential and connected layers namely input, hidden and output layers [1, 24]. The input layer accepts the data features and transmit the information to output layer by way of hidden layer [1]. The hidden layer process the data based on its connection to the input layer and the weights belonging to these connections. The output layer classifies the data into categories [1]. Because there is no analytical method for the determination of the ideal number of neurons in the hidden layer, it is found through experimentation [1, 24].

The ANN classifier has been designed as a pattern recognition network with resilient backpropagation training function. The network has one input layer, one hidden layer with 100 neurons and one output layer where the objects are classified into 3 groups. The features of impurities and the features of type-1252 wheat grains determined as vitreous and as non-vitreous by an expert have been obtained from separate videos and used as training data for the ANN to classify the objects in a video visualizing a mixture of vitreous, non-vitreous wheat grains and non-wheat materials meaning the network is trained by supervised learning approach where the inputs with their targets are known. The image data sample used for the training is shown in Fig. 10.

The input layer accepts 25 features of 9000 vitreous, non-vitreous wheat grain and non-wheat material samples as input and classify them into 3 categories. Training, test and validation data have been chosen randomly by the percentage of 90, 5, and 5 in the ANN training algorithm. The training data ANN classifier has been designed as a pattern recognition network with resilient backpropagation training function and hyperbolic tangent sigmoid as a transfer function, because a transfer function in a backpropagation learning needs to be continuous, smooth and its derivation is easily retrievable, it can saturate which means it has a minimum and a maximum output value also it needs to be nonlinear but it can be linear as well if the network weights are small [25]. The network performance graph, error histogram graph is shown in Fig. 11. The training, test, validation and overall receiver operating characteristic graph is shown in Fig. 12. The training, test, validation and overall confusion matrices are shown in Fig. 13.

Fig. 10 Images of the training data; vitreous wheat, non-vitreous wheat and non-wheat materials

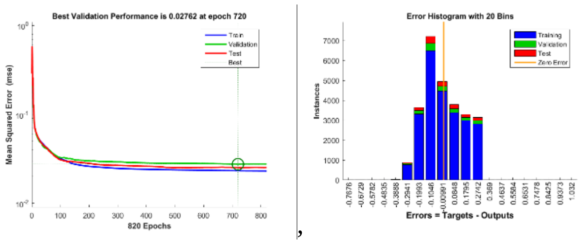

Fig. 11 Network performance and error histogram

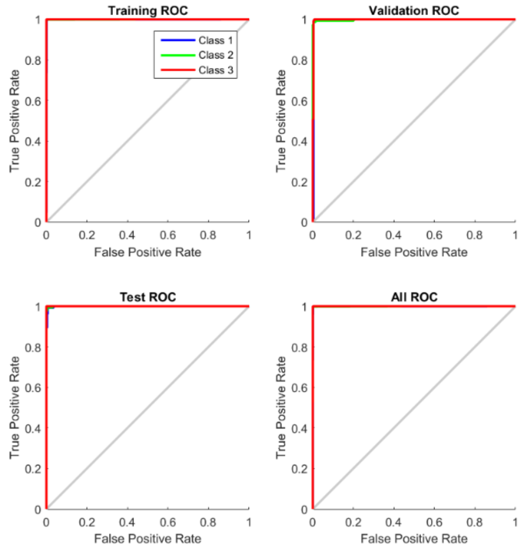

Fig. 12 Training, Test, Validation and All ROC

Fig. 13 Training, Test, Validation and All Confusion Matrix

III. Results and discussions

After the training of the network based on the feature data of reference wheat grains and non-wheat materials, a function has been generated from the ANN and it has been used for classification of the objects in a video where the objects are the mixture of vitreous and non-vitreous wheat grains and non-wheat materials. The results of the ANN function have been compared with the training results within certain boundaries and the mixture of objects have been classified into three groups. The obtained success rate was 91.66%.

IV. Conclusions

As it is shown in literature, previous studies conducted are generally not about the purification of wheat grains from non-wheat materials but about classification of wheat varieties and the studies were rare where the quality classification of one type wheat based on its vitreousness was conducted. Also, the studies realized in a dynamic environment are almost non-existing. In this study, the objective has been to obtain good quality type-1252 durum wheat by classifying vitreous and non-vitreous wheat grains and discriminating the non-wheat materials in a dynamic system using image processing techniques. These processes are image pre-processing for image enhancement, watershed transform with extended-minima transform for segmentation, blob analysis for feature extraction and ANN for classification.

In this study, the obtained success rate was 91.66% which is not close to 100%. However, if it is considered that there are not many studies conducted in a non-stationary environment, the success rate is much promising. Most studies conducted in a non-stationary environment realizes the image processing by repeatedly stopping the conveyor belt and taking image samples or arranging the objects in a proper order and not continuously. So, in this study there are classification errors on the boundaries of the frames. If an object tracking method is used in future studies, the success rate will surely improve. Also, it will be tried using different classification methods to see if the result gets better and the determination of most significant features will be realized.

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