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EFFICIENT APPROACH OF DETECTION AND VISUALIZATION OF THE DAMAGED TABLETS

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ABSTRACT

People affected by many diseases in their lives and this effect with the productivity of the individual in society and the lives of the entire person and most of these diseases can be cured by medicines. The problem in pharmaceutical industries, in the actual situation, existing a number of defects incorporated in tablets inadequate fines to granules ratio, inadequate moisture content and poor machine settings can be some of the reasons for those visual defects such as faults in a cover of tablet pill. In addition, the production of medicines and pharmaceutical factories are expanded so it is difficult to control the quality of the tablets after packaging. The aim of this paper is to upgrade this manual tablet-sorting machine into an automated system with the aim of improving the speed and accuracy of the sorting process. The hole in the cover plastic package is common defects that can be found in tablets. Therefore, this defect was considered for the purpose of this paper. Damage on the Cover plastic package can be produced during the production of the packaging and can be produced before packaging therefore; will design system inspection the cover plastic before packaging for less damage money as much as possible, also inspection the cover plastic after packaging because the damage on the cover plastic packaging causes damage in pills and capsules. The proposed system algorithm includes preprocessing and feature extraction using opponent local binary patterns &opponent coordinated clusters representation (its the contribution research) and finally the classification of tablets for damage or undamaged issue using an artificial neural network algorithm (ANN) and specifically feed forward back propagation learning.The neural network training with feature extraction from the data after it has been tested. The experimental results are acceptable, the performances of the check pill cover plastic system indicated the total accuracy of 94.4% for testing. Also, the approach using opponent features provides better recognition accuracy than other approaches. The system is evaluated using sensitivity, specificity, and accuracy. The programs are done using Matlab package.

Keywords: *Hole in the Covered Plastic, LBP, CCR, Packaging, Texture.*

1. INTRODUCTION

Packaging is defined as the set of different components which edge the pharmaceutical product from the time of production until its use. Packaging pharmaceutical products is a wide, encompassing, and multifaceted task. Packaging is responsible for providing life‑saving medicine, medical devices and medical treatments [1, 2].

Pharmaceutical tablets are solid, even or biconvex dishes, unit dose form, prepared by compressing a drug or a mixture of drugs, with or without diluents. They vary in shape and differ very in size and weight, depending on quantities of medicinal item and the meant mode of rule. It is the most popular dosage form and 70% of the total medicines are dispensed in the form of the tablet. All drugs are available in the Tablet form, except where it is difficult to formulate or administer [3].

Tablets and capsules are widely manufactured and prescribed and may provide a number of advantages over other dosage forms, including ease of storage, portability, ease of administration, and accuracy in dosing. While generic formulations of these drug products are required to be both pharmaceuticals and therapeutically equivalent to a reference listed drug (RLD) [4]. They are worried that distinctions in physical attributes (e.g., gap in cover plastic of the tablet or case) may influence quiet consistence and worthiness of medicine regimens or could prompt solution blunders. We trust these patient wellbeing concerns are critical, and we are prescribing that nonspecific medication makers consider physical properties when they create quality target product profiles (QTPPs) for their bland item hopefuls [5].

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Distribution of products is now more global than ever. Mass customization of packaging to permit its utilization in multiple markets is a topic that needs piece and discourse. Environmental issues, including sustainability, will always be a subjective dimension to any packaging design [6].

In this study, the researcher concentrates on the damage in the cover plastic as this type of damage effect on medicine. To detect damage in the plastic package will use a texture feature as factor to classify if tablet damage or not.

This research tries to proof affect texture feature LBP and CCR to the inspection cover plastic package if damage or safety.

2. REESERCH OBJECTIVES

The aim of this paper is to extract an opponent features texture pattern from packages of pill and capsule and to use texture descriptors to classify the package into safety or damage. Artificial neural network (ANN) is used to perform the classification and compare their results in terms of accuracy.

The performance of this method is measured by the sensitivity, specificity, and accuracy which can be viewed as the ratio of the number of packages correctly classified over the total number of test package using texture descriptors as input to machine learning techniques. Finally, our study deals with package plastic of pill and capsule classification using NN and comparing their performance.

3. COVER PLASTIC PACKAGING DETECTION SYSTEM

Quality is essential for customer satisfaction and offer of products in the focused market. Present day consumers have a wide variety of demands and needs leading to increased complexity in a variety of products. The price war, high quality, traceability, necessity of disclosure of quality, the norms and regulations, impose the manufacturers to have a flexible design with zero defects in a highly competitive market. To accomplish the high caliber that is requested by the clients, makers and their providers must depend on Machine Vision to avert absconds at different phases of generation. Machine Vision has turned into a fundamental piece of the pharmaceutical business, because of the controls and the wellbeing impacts [8].

In 2004, U.S. Food and Drug Administration (FDA) released guidance for industry document (PAT-A Framework for Innovative Pharmaceutical Development, Manufacturing and Quality Assurance), in which they recommend the use of a quality-by-design paradigm (QbDP) in the pharmaceutical industry. The document encourages the pharmaceutical industry to employ new techniques in order to measure critical process parameters on– an in-line, to obtain a better control over the manufacturing processes; consequently, decreasing the risk of faulty products [9].

The visual appearance of the pharmaceutical tablets is one of the critical quality parameters, which is these days controlled via computerized visual investigation machines after the assembling procedure [10, 11]. Authorizes the pharmaceutical organizations to deliver tablets with dynamic substances and measurements unambiguously controlled by tablet estimate, shape, surface, engrave or potentially other visual and physical attributes. Other than recognizable proof, visual appearance assumes a vital part in the promoting of certain pharmaceutical items as the flawed appearance of a solitary tablet in a bundle can raise genuine questions about the uprightness and nature of the product [12].

3.1 Functions of Pharmaceutical Packaging

The pharmaceutical packaging involves the following functions:

1. Containment: The containment of the most major capacity of packaging for medicinal products. The outline of high-quality bundling must consider both the requirements of the item and of the assembling and appropriation system. This requires the packaging: not to leak, nor allow diffusion and permeation of the product, to be strong enough to hold the contents when subjected to normal handling and not to be altered by the ingredients of the formulation in its final dosage form [7].

2. Protection: The packaging must secure the product against all adverse external influences that may affect its quality or potency, for example, light, dampness, oxygen, natural tainting, mechanical harm and counterfeiting/adulteration [6].

3. Presentation and information: Packaging is likewise a fundamental wellspring of data on therapeutic products. Such data are given by marks and package inserts for patients [6].

4. Identification: The printed packs or its subordinate printed segments serve the elements of giving both personality and data. [6].

5. Convenience: The comfort is related to product use or administration, e.g., a unit measurement, eye drop which both disposes of the

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requirement for additive and lessens dangers related by cross contamination, by managing just a single dose [6].

3.2 Categories of Pharmaceutical Packaging Materials

The Categories of Pharmaceutical packaging is divided into [6]:

1. The primary packaging system is the material that first envelops the product and holds it, i.e., those package components and subcomponents that actually come in contact with the product, or those that may have a direct effect on the product shelf life e.g., ampoules and vials, prefilled syringes, IV containers, etc.
2. Secondary packaging system is outside the primary packaging and used to group primary packages together, e.g., cartons, boxes, shipping containers, injection trays, etc.
3. The tertiary packaging system is used for bulk handling and shipping e.g., barrel, container, edge protectors, etc.

4. METHODOLOGY

4.1 Material

Images are collected via high-resolution camera to capture Red Green Blue (RGB) color images. The acquisition of a color image with real color is an important part of the system to ensure the correct image resolution. In this paper, the image databases of pills and capsules that have been adopted are obtained by taking an image by camera Nikon 90. The database contains about 322 color images for a tablet of pills and capsules, images are captured in the JPEG format with maximum resolution size 75x75 pixels. MATLAB software was used to perform image processing and image analysis.

Figure.1 show in the first row the samples of the safety package while the second row shows samples of damage package.

Figure 1*: Safety (first row) and damage (second row) samples.*

4.2 Methods

4.2.1 The Proposed Framework

Plastic package is commonly used for the packaging of pill in the pharmaceutical companies. The damage in the cover plastic package can be produced during the production of the packaging and can be produced before packaging therefore; will design system inspection the cover plastic before packaging for less damage money as much as possible, also inspection the cover plastic after packaging because the damage on the cover plastic packaging causes damage in pills and capsules. The proposed method will include three steps such as the preprocessing, Compute texture feature (LBP&CCR) and NN classification (safety and damage). The researcher's proposed method for inspecting the cover plastic packaging is in the stages of the proposed framework. The processed can be divided into many major stages as presented in Figure 2.

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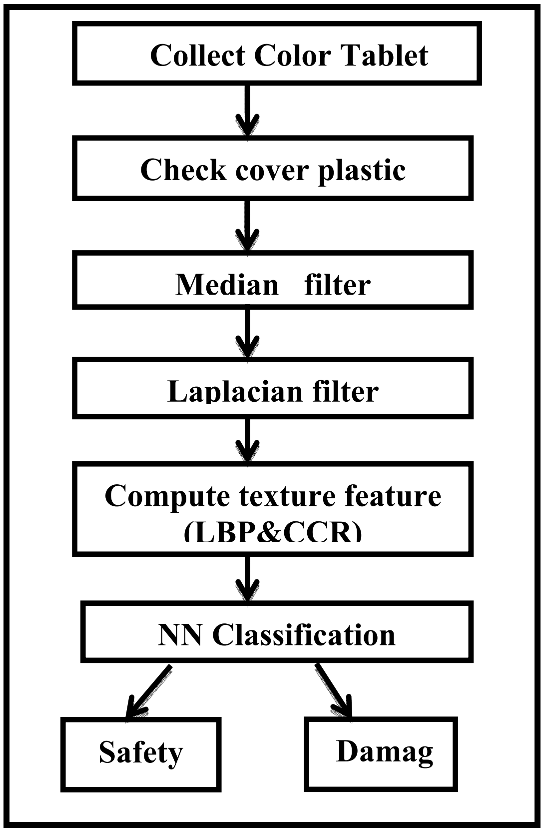

***Figure 2**: Proposed system*

A. Preprocessing

Light reflections from the blisters and background makes inspection results unstable and low. Therefore, preprocessing image necessary to remove halation caused by the blister pack and reduce the computational time, eliminating many of the effects of changing illumination and reduce the effect of the noise, will use two filters. Median and Laplacian filter. Median filtering is done on the image with a kernel size of [3x3] to remove random noise. This filter is an order statistic filter which replaces the value of a pixel by the median of the pixel values in a small neighborhood:

$$F(x, y) = \text{median}\{g(u, v)\} \quad (1)$$

Where (u, v) ϵ S (x, y) the neighborhood around (x, y) [13].

The median filter use for erasing impulse noise. It causes the impulse noise in the background is disappearing, but also an extra consequence is blurring the edges. This effect could neutralize impressively by applying the Laplacian sharpening spatial filter Laplacian sharpening spatial filter using for highlighting fine details and enhance them which are blurred such as edges. As you know, Laplacian is a linear and rotation invariant operator [14].

The purpose of using a Laplacian sharpening spatial filter is for highlighting fine details and enhances them which are blurred such as edges. Also, Laplacian filters are derivative filters used to find areas of rapid change (edges) in images Figure 3 show preprocessing steps.

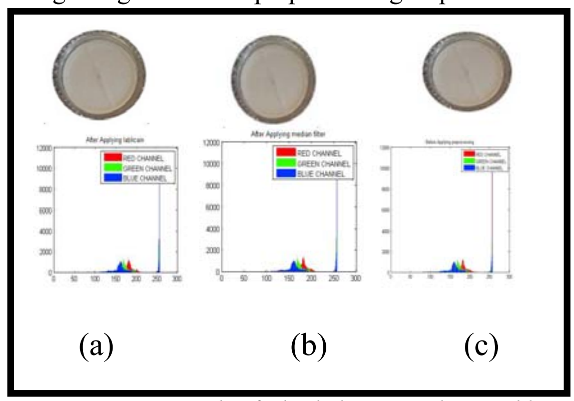

***Figure 3**: Sample of Check the cover plastic tablet image after applying the (preprocessing steps). (a) Original image. (b) Apply median filter (c) applies Laplacian filter.*

B. Texture Analysis

Texture is commonly used feature in the analysis and interpretation of images [15]. Texture analysis has an important role in computer vision and pattern recognition [16]. Also, Texture examination is a vigorous part in investigation of pattern appreciation [38].

The texture classification process involves two phases: the learning phase and the recognition phase. In the learning phase, the target is to build a model for the texture content of each texture class present in the training data, which generally comprises of images with known class labels. The texture content of the training images is captured with the chosen texture analysis method. In the recognition phase the texture content of the unknown sample is first described with the same texture analysis method. Then the textural features of the sample are compared with those of the training images with a classification algorithm, and the sample is assigned to the category with the best match [17].

Many recognitions /classification systems require a previous learning or modeling task to obtain the feature vectors, which characterize the objects of interest before classification can take place, the process which allows us to compute these

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features, called feature extraction [18]. The features can be extracted either directly from image statistics or spatial frequency domain [19].

Texture is an important characteristic for the analysis of many types of images [20] also, Texture analysis is important in many applications of computer image analysis for classification or segmentation of images based on local spatial variations of intensity or color. A successful classification or segmentation requires an efficient description of image texture. Important applications include industrial and biomedical surface inspection, for example for defects and disease, ground classification and segmentation of satellite or aerial image, segmentation of textured regions in document analysis, and content-based access to image databases. However, despite many potential areas of application for texture analysis in industry, there are only a limited number of successful examples. A major problem is that textures in the real world are often not uniform, due to changes in orientation, scale or other visual appearance. In addition, the degree of computational complexity of many of the proposed texture measures is very high [21].

Texture analysis system that's used for texture classification, segmentation, or labeling should consist of two phases: (i) features extraction phase, and (ii) texture discrimination [22].

Due to the extensive research on texture analysis over the past 30 years, it is impossible to list all published methods with reference to several texture analysis survey papers [23, 24, 25, and 26]. The categorization of texture analysis techniques falls into four ways: statistical approaches, structural approaches, filter based approaches, and model-based approaches. Clearly, statistical and filter based approaches are very common [27]. Most of current approaches to texture feature extraction problem employ statistical methods [28]. In this paper used Statistical Approach LBP and CCR to feature extraction, The reason why this family of texture descriptors (LBP and CCR) is chosen among the vast plethora of features currently available is multiple-fold First, these techniques offer an excellent approach to analyze the texture at the micro level by analyzing the distribution of the local texture elements (local binary patterns) and in addition they entail a low computational overhead, a fact that makes them attractive when applied in the implementation of real-time industrial applications. Thus, by using these techniques one could achieve real-time processing in a manufacturing plant, this allows feature extraction from cover plastic packaging at a higher rate. Second, the local binary pattern related techniques are parameter-free and as a result, they do not require complex optimization procedures, as many other methods do. Third, the LBP texture descriptors are intrinsically invariant to changes in illumination intensity and monotonic image transforms. Fourth, these features have been proven to be effective and accurate in discriminating texture.

RGB color space is used instead of gray level because it contains the color information are greater than the gray level.

- **Local Binary Pattern**

The original local binary pattern (LBP) operator, introduced by Ojala et al., provides a robust way of describing local texture in a 3x3 neighborhood [29]. For each pixel in the image, a binary label can be obtained by comparing the center pixel with each of its neighbors. The Binary label can then be represented by a numeral label using predefined weights for each of the neighboring samples. Using a 3x3 neighborhood, a maximum of 256 (2^8) Textures can be described. The occurrence of texture labels over a predefined region, are used to create a Histogram describing the local texture. LBP have previously been applied with promising results in multiple areas, ranging from face detection [30] to identification of liver disease [31].

A limitation of the original operating has been its small spatial support area, due to its 3x3 neighborhood. Features found in this neighborhood cannot capture large structures in the texture, which could be a dominant. As a solution, extensions of the operator were introduced by Ojala et al. To facilitate for uniform patterns and a rotation invariant analysis of image textures at multiple scales [32]. The **principle** of work LBP is Given an arbitrary image pixel, its circular neighborhood can be described using a radius r and a fixed number of samples along the circle. By a comparison of each sample in the circular neighborhood with the center sample, a binary label is set to illustrate if samples are above or below the threshold defined by the center sample, as shown in figure 4.

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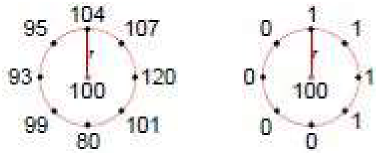

***Figure 4**: LBP: principle*

A numeral label is found using individual weights to each sample in the neighborhood, corresponding to figure 5.

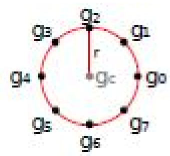

***Figure 5**: LBP: weights*

Where each weight is defined by:

$$gp = 2^P \tag{2}$$

The LBP operator is denoted LBPP; R, where P is the number of neighbors and R are the operator radius. The operator can then be defined as:

$$LBP, R=\sum_{p=0}^{P-1} S(gp-gc)2^P \tag{3}$$

Where s (x) is the logic function defined by:

$$S(x)=\begin{cases}1 & if\ x \geq 0\\ 0 & if\ x < 0\end{cases} \tag{4}$$

In the case where neighboring samples does not fall in the center of an image pixel, bilinear interpolation is used. A histogram of the texture descriptors in a defined region is used to identify regions or known textures in images. **Rotation Invariance** An extension of the original operator is the introduction of rotation invariance [33]. As texture orientation often can be arbitrary, a rotation invariant way of describing the texture is desired. Using figure 5 as an example, LBP gives the binary pattern 10000111. With various orientations of the texture, the center pixel can be described by a total of eight different neighborhoods, illustrated in figure.

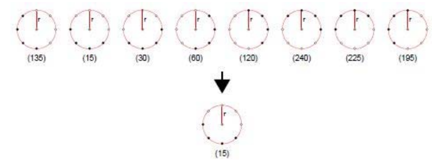

***Figure 6**: LBP: Rotation invariance principle*

The gray circle is defined as the center pixel, black circles as zeros and white circles as ones. By applying weights, the eight numeral values are obtained. The rotation invariant descriptions using the minimum of the possible descriptors are then being described using:

$$LBP^{ri}_{P,R} = \min \{ROR (LBP\ P, R, i)\ i = 0., P-1\} \tag{5}$$

Where ROR is a rotate operation, used to find the P possible rotations of the LBP label.

The minimum value found is 15, corresponding to the binary pattern 00001111 illustrated in figures 6. **Uniform** A second extension of the original operator is uniform patterns [102]. Ojala et al. Observed in their experiments that the nine uniform patterns in LBPriu28; 1, where riu2 denotes rotation invariant uniform patterns with a maximum of 2 binary transitions, contributed on average to 87:2 and 89:7 percent of all patterns. In the case of LBPriu2 16;2, the 17 uniform patterns contributed on average to 66:9 and 70:7 percent of all patterns in the image. Pattern uniformity, U (LBPP;R), is given by equation 6, and describes the number of transitions between zero and one in the local binary pattern. For example, the pattern 00011000 and 00001111 contain two transitions while 01101100 contain four transitions.

U(LBP;R)=|s(gp-1-gc)-sg0-gc)|+

$$\sum_{p+1}^{P-1} |s(gp-gc)-s(gp-1-gc)| \tag{6}$$

The local binary pattern is denoted u2 if the pattern uniformity is equal to two or less. With P neighbors, P + 2 possible bins for rotation invariant uniform patterns are defined. Where the number of uniform patterns is P + 1 = 9 and the last bin describes all other patterns.

$$LBP^{riu2}_{P,R} = \begin{cases}\sum_{p=1}^{P-1} s(gp-1-gc) & if\ U(LBP,R) \leq 2\\ P+1 & otherwise\end{cases} \tag{7}$$

Figure7 illustrates the proposed bins and their corresponding uniform patterns, using the LBP

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operator with eight neighbors. Black circles illustrate zeros and white circles illustrate ones.

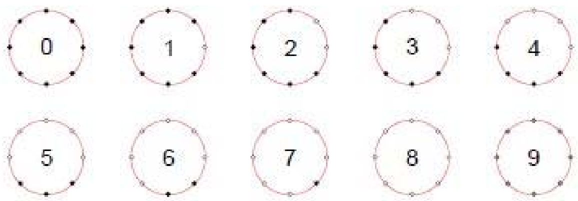

Figure 7: LBP: Uniform rotation invariant descriptor bins

Local Binary Patterns (LBP) have emerged as one of the most prominent texture descriptors, attracting significant attention in the field of computer vision and image analysis due to their outstanding advantages:

1) Ease of implementation

2) Invariance to monotonic illumination changes, and Low computational complexity.

Although originally proposed for texture analysis, the LBP method has been successfully applied to many diverse problems, including dynamic texture recognition, remote sensing, fingerprint matching, visual inspection, image retrieval, biomedical image analysis, face image analysis, motion analysis, edge detection, and environment modeling [34] [35].

In this paper Color LBP feature extraction operators are using in order to increase invariance property and discriminative power of the original LBP operator or instead of using a grayscale level. Also, apply calculate in each channel separately (Red, Green and Blue) the rotation invariant versions LBP81 using formula 7 this manner is apply on each color channel separately, in this manner the descriptor becomes more compact since the number of bins of the histogram reduces to 36. To provide better recognition calculating the opponent color LBP each pair of the color channels uses in collecting opponent color patterns so that the center pixel of a neighborhood and the neighborhood itself are taken from different color channels illustrates the three situations in which the center pixel is taken from the red channel. In total, three inter-channel LBP histograms and six intra-channel histograms are extracted and concatenated into a single distribution. Since opposing pairs, like R-G and G-R, are highly redundant, either will suffice for analysis. Consequently, three of the six inter-channel histograms can be discarded. Even then, the resulting texture descriptor is six times longer than the grayscale version. For a pair of channels (*u, v*) the resulting Opponent Color Local Binary Patterns (OCLBP) can be defined as follows:

$$F\ OCLBP\ u,v\ (P) = \sum_{i=0}^{P-1} 2^{i}\ \varphi\ (p0,\ u,\ pi,\ v) \quad (8)$$

Where p*i, v* indicates intensity of the *i*-th pixel in the *v*-th channel. In the RGB space the image representation is the concatenation of the feature vectors generated by OCLBPR, R, OCLBPG, G, OCLBPB, B, OCLBPR, G, OCLBPR, B and OCLBPG, B. The resulting vector is therefore six times larger than LBP's. **Algorithm (1)**: for the Local binary pattern (LBP) feature extraction from color cover plastic tablet image.

Algorithm (1)Computes texture features.
Input: a color image which results from the preprocessing step of cover plastic tablet image. **Output**: Texture feature vector.
Step1: read color image. **Step2**: separate image into 3-channels. **Step3**: Divided each channel into 3*3 blocks for every single pixel in the cell, compare the pixel to each of the 8 neighborhood. Follow the pixels along the circle. **Step4**: calculating LBP using formula 3. **Step5**: calculate in each channel separately (Red, Green and Blue) the rotation invariant versions **Step6**: calculating the opponent color LBP: each pair of the color channels is use in collecting opponent color patterns **Step 7:** Save 216 features for LBP with matrix.

- **CCR Feature Extraction**

The Coordinated Clusters Representation (CCR) is a method based on global binarization of the input image. In order to preserve textural information, care must be taken in the computation of an adequate threshold. This model represents textures through the probability of occurrence of the 512 elementary binary patterns that can be defined in a 3×3 binary window [39]. The

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dimension of these elementary patterns is usually set to 3 x 3 pixels, since this size provides good discriminative power at a reasonable cost in terms of both computing speed and memory usage. In this case, the feature vector –denoted by CCR 3 x 3 has 2^9= 512 components. This binary texture descriptor was later extended to grayscale texture images through thresholding [40, 41]. In practical applications, it is important that features are invariant against rotation, since images are rarely captured under steady viewing conditions. Rotation-invariant CCR features can be obtained following an approach similar to the one proposed for the LBP3x3 operator [31]. The first step consists in replacing the squared neighborhood of the CCR 3x3 by a circular one. The intensity of the pixels that are not placed exactly on pixel positions is estimated through bilinear interpolation. This model is denoted by CCR8. In order to achieve rotation invariance, all those patterns that are rotated versions of the same pattern are mapped to the same primitive pattern [42].

In this paper Color CCR feature extraction operators are using in order to increase invariance property and discriminative power of the original CCR operator or instead of using a grayscale level. Considering that to enhance an 8-bit LBP circular patterns by adding the central pixel, then two 9-bit CCR circular patterns and calculate in each channel separately are obtained (Red, Green and Blue). The rotation invariant versions CCR this manner is apply on each color channel separately. In this manner the descriptor becomes more compact since the number of bins of the histogram reduces to 72. To provide better recognition Calculating the opponent color CCR: each pair of the color channels uses in collecting opponent color patterns so that the center pixel of a neighborhood and the neighborhood itself are taken from different color channels illustrates the three situations in which the center pixel is taken from the red channel... In total, three inter-channel CCR histograms and six intra-channel histograms are extracted and concatenated into a single distribution. Since opposing pairs, like R-G and G-R, are highly redundant, either will suffice for analysis. Consequently, three of the six inter-channel histograms can be discarded. Even then, the resulting texture descriptor is six times longer than the grayscale version. For a pair of channels (u, v) the resulting Opponent Color CCR (OCCCR) can be defined as follows:

$$F\ \mathrm{OCCCR}\ u, v\ (P) = \sum_{i=1}^{n} 2^{i} - 1\ \varphi\,(p0, u, pi, v) \quad (9)$$

Where pi, v indicates intensity of the i-th pixel in the v-th channel. In the RGB space the image representation is the concatenation of the feature vectors generated by OCCCRR, R, OCCCRG, G, OCCCRB, B, OCCCRR, G, OCCCRR, B and OCCCRG, B. The resulting vector is therefore six times larger than CCR's. **Algorithm (2)**: for the CCR feature extraction from color cover plastic tablet image.

Algorithm (2) computes texture features (CCR).
Input: a color image which results from the preprocessing step of cover plastic tablet image. **Output**: Texture feature vector.
Step1: read color image. **Step2**: separate image into 3-channels. **Step3**: Divided each channel into 3*3 blocks for every single pixel in the cell, compare the pixel to each of the 8 neighborhood. Follow the pixels along the circle. **Step 4**: Apply the opponent color CCR **Step4.1**: considering that to enhance an 8-bit LBP circular patterns by adding the central pixel we get two 9-bit CCR circular patterns and calculate in each channel separately (Red, Green and Blue) the rotation invariant versions CCR this manner is apply on each color channel separately **Step5**: calculating the opponent color CCR: each pair of the color channels is use in collecting opponent color patterns. **Step6**: Save 432 features for CCR with matrix

- **Combination**

Since LBP and CCR contribute to determine the texture features, it makes sense trying to join them together to improve system accuracy, combine LBP+CCR (648 features).

***TABLE 1**: FEATURES VECTOR COVER PLASTIC TABLET.*

Textures feature		
CCR+LBP	LBP	CCR
648	216	432

C. Classification

Classification is an important stage in

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identifying package into safety or damage. In classification classifier is used for object recognition and classification. The classifiers recognize the object and classify based on the extracted features of an image given as an input. There are two important phases in the classification. They are training and testing phase. In the training phase, the pre-determined data and its associated class labels are used for classification**.** In this paper use an artificial neural network to classify packages into safety or damage. The Structure of the Neural Network include Create a feed forward neural network with one hidden layer, 60 neurons in each hidden layer; the input layer of the neural network is identified by characteristics of the inputs. 648 feature vectors are obtained. Therefore, a number of neurons in the input layer are 648, and output layer neuron determined by the number of classes. Two classes (safety and damage) are obtained, therefore the number of neurons in the output layer is two. The important parameter, learning rate equal to 0.00001, epochs equal to 10000, maximum number of iterations, training times infinity, data division function (divide block), the transfer function of its layer hyperbolic tangent sigmoid transfer function is used 'tansig', the linear activation function is selected for output layer 'purlin', performance function, default = 'me 'and training function is back propagation function, weight and bias are generating random. Training the network by train data and target matrix, target matrix is a matrix with two rows and two columns, each row consists of a vector of zero values except a 1 in element i, where i is the class they are to perform. Also, compute the network performance and simulates the neural network by taking the training net, Validation net and test data return the indices to the large output as class predicts.

5. EXPERIMENTAL RESULTS

Table 2 refers to the all the classification results when testing the program by using texture features with (LBP) only, texture features with (CCR) and with Combination texture features (LBP) & texture features (CCR)**,** The network structure with one input layer, one hidden layer and two output layer.

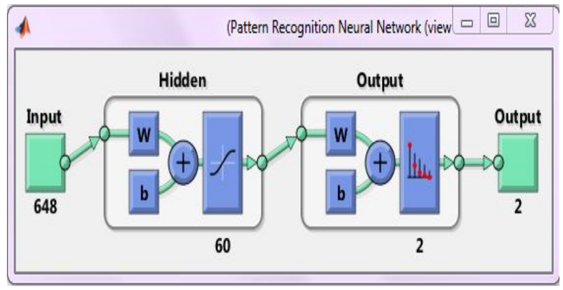

Figure 8*: The neural network structure of classifier texture (LBP+CCR) features*

Figure 8 shows the network structure with one input layer, one hidden layer and two output layer. It is the 648×60×2 network structure. The input vector is 648. The output vector is two. This paper uses the above ANN architecture, feed forward-back propagation learning algorithm to generate: train, validate and test the neural network for a cover plastic tablet. MATLAB software with its neural network toolbox is used. Data sets are portioned into three subsets, training set, validation and testing set. The network gives high accuracy when train equal to 95.7 % and test equal to 94.4 % with a simple training time equal to (0.1 seconds) at 24 epochs, with best validation performance is 0.37314 at epoch 18 see Figure 9.

To evaluate performance will use sensitivity, specificity, accuracy and ROC that will explain in details in the 5.2 and 5.3 section.

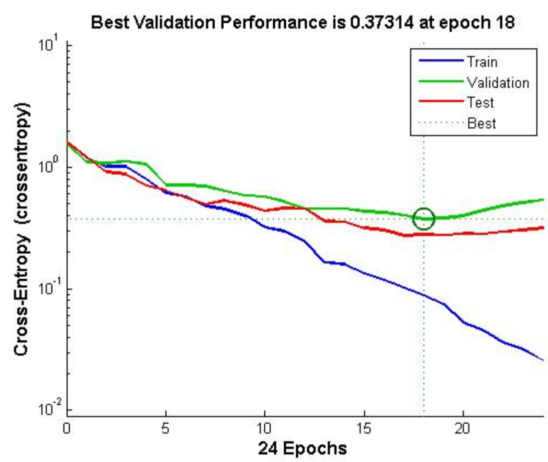

Figure 9*: best validation performance*

***Table 2**: show all the classification results*

Data type	Feature type	Classification Accuracy %
		Test Data
Tablet image	Texture features (LBP)	90.7
Tablet image	Texture features (CCR)	91.9
Tablet image	Combination texture features (LBP) & texture features (CCR)	94.4
Total accuracy from the NN by using texture features (LBP) & texture features (CCR)		**94.4**

***Figure 10**: the confusion matrix for showing results the training of NN*

5.1 Confusion Matrix (Classification Matrix)

The performance of classifier is analyzed using confusion matrix which is also known as table of confusion. It displays the number of correct and incorrect predictions made by the model compared with the actual classifications in the test data. The confusion matrix lists the correct classification against the predicted classification for each class. The number of correct predictions for each class falls along the diagonal of the matrix. All other numbers are the number of errors for a particular type of misclassification error as mentioned by [36] Sharma, A., & Arora, S. in (2012).

In Figure 10 can see that there are few misclassifications due to which there is a minimum drop in accuracy. In lower triangular matrix there is no misclassification. Similarly, an upper triangular matrix class 1 was misclassified by 3.1%and again one time as class 2 by 1.2%. Also can see that the green boxes represent the final accuracy for each class as each class was correctly trained. Out of 648 columns of data set 322 have been used for training purpose. Finally, overall accuracy is shown in blue box which shows that each class classification was correctly learned by Scaled conjugate gradient backpropagation classifier with zero mean square error and within stipulated parameters and gives 95.7 % results.

In figure 11 can see that there are few mis-classifications due to which there is a minimum drop in accuracy. In lower triangular matrix there is no mis-classification. Similarly, an upper triangular matrix class 1 was mis-classified by 3.7% and again one time as class 2 by 1.9%. Also can see that the green boxes represent the final accuracy for each class as each class was correctly trained. Out of 648 columns of data set 322 have been used for testing purpose. Finally, overall accuracy is shown in blue box which shows that each class classification was correctly learned by Scaled conjugate gradient backpropagation classifier with zero mean square error and within stipulated parameters and gives 94.4 % results.

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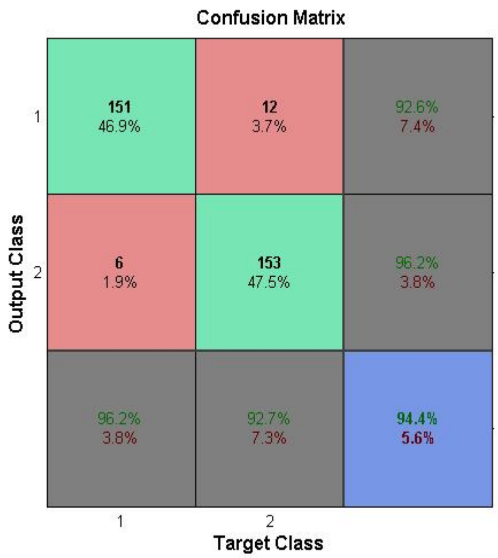

***Figure 11**: the confusion matrix for showing results the testing of NN*

5.2 Performance Evaluation Measure

The proposed techniques, performance are evaluated in expressions of sensitivity, specificity, and accuracy. The three expressions determined as follows:

- Sensitivity is used to measure the ratio of positives that are correctly identified; the result denotes positively (damage). It is computed as the following equations:

$$\text{Sensitivity} = \frac{TP}{(TP+FN)} * 100\% \qquad (10)$$

- Specificity is used to measure the ratio of negatives that are correctly identified; the result denotes negatively (safety). It is computed as the following equations:

$$\text{Specificity} = \frac{TN}{(TN+FP)} * 100\% \qquad (11)$$

- Accuracy is used to measure the eventuality which the classifies test is performed correctly. It is computed as in the following equations:

$$\text{Accuracy} = \frac{(TP+TN)}{TP+TN+FP+FN} * 100\% \qquad (12)$$

Where TP is True Positives that correctly classify positive cases; TN is True Negative that correctly classify negative cases, FP is False Positives that incorrectly classify negative cases, and FN is a False Negative that is incorrectly classifies positive cases. The higher the sensitivity and specificity are more accurately the classifier as mentioned by [36] Bukovec in 2007.

When classification is done results may have an error rate, whether fail to identify a safety or damage. The performance measure to the is done by the expressions of true and false positive, true and false negative, sensitivity, specificity, and accuracy that are computed for ANN classification by using the equations 10, 11, and 12 respectively.

***Table 3**: Performance Parameters of testing.*

Performance Parameters	Performance%
Sensitivity	88
Specificity	95.74
Accuracy	91.75

5.3 Performance Evaluation Measure for the Check the Cover Plastic Tablet Recognition with ROC

The ROC curve relates the tradeoffs between the true positive (TPR) and the corresponding false positive (FPR) defect detection rate of each feature. The TPR=TP/P is a ratio between the number of correctly detected tablets with defects (TP) and all defective (P) tablets, while the FPR=FP/N represents a ratio between the number of incorrectly detected non-defective tablets (FP) and all non-defective (N) tablets. TPR is a measure of sensitivity, while FPR is a measure of defect detection specificity [36].

When classification is done results may have an error rate, whether to fail identify a safety or damage cover plastic. The performance measure to the classify cover plastic is done by the expressions of the ROC. The created area below the graph of Check the cover plastic tablet system was near from (1) that shows a good efficiency of the system. ROC chart was also calculated equal to near from 1. This indicates the system nearest from a perfect system. Figure 12shows the ROC of classification check cover plastic

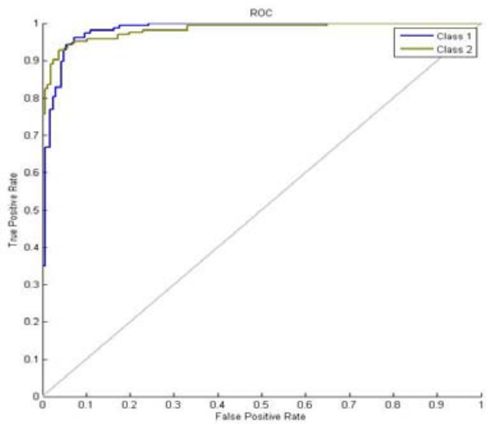

Figure 12*: shows the ROC of classification check cover plastic*

6. CONCLUSION

This paper presented a comparative study of the performance of inspection cover plastic package pill and capsule using different feature set i.e. LBP texture and CCR texture. Our inspection cover plastic package pill system passed all the significant dataset protocols to ensure all classification parameters such as sensitivity, specificity and accuracy for all feature set. Further, it shows the dominant behavior of higher combination LBP&CCR. Overall, this study shows encouraging results. Supports machine learning gives strong for classification with ANN. The result shows Median filter applied to enhance image with little smoothing and remove the noise. Laplacian filter is used to enhance contrast of the image and get preferable performance for texture features. Also, feature extraction is very important stage for classification accuracy. In addition, feature extraction from color images are given the powerful for classification and following-up. Also, the performance achieved by NN algorithm is excellent for databases and approve the supremacy of that classifier. These methods may help to improve detection of the damage in the packaging.

The proposed method is easy to integrate and it will also eliminate the need of sophisticated mechanical fixtures for testing these tablets.

In future works we intend to replace Neural Network with many more optimization techniques that may offer more options in results and accuracy e.g. Support vector machines and, finally, apply the proposed system in a real situation in the company used as a case study.

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[3] Reference listed drug means the listed drug identified by FDA as the drug product upon which an applicant relies in seeking approval of its ANDA. See 21 CFR 314.3 (b). FDA publishes the identification of RLDs in the Approved Drug Products with Therapeutic Equivalence Evaluations (i.e., Orange Book).

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