# Recognition and Classification of Different types of Food Grains and Detection of Foreign Bodies using Neural Networks

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## ABSTRACT
This paper deals with the classification of bulk food grain samples and detection of foreign bodies in food grains. A new method for inspecting food samples is presented, using ANN and segmentation to classify grain samples and detect foreign bodies that are not detectable using conventional methods easily. A BPNN based classifier is designed to classify the unknown grain samples. The algorithms are developed to extract color, texture and combined features are extracted from grains and after normalization presented to neural network for training purpose. The trained network is then used to identify the unknown grain type and it's quality in terms of pure/impure type. A Segmentation based detection model is developed to detect the foreign body in the impure grain samples. This model accepts an impure grain samples, pre-processes and segments the image using two different thresholds T1 and T2 to detect the foreign body in impure image. Finally the success rates are observed from both classification and foreign body detection models and are recorded.

**Keywords**: artificial neural networks, classification, color, segmentation, texture feature extraction.

## 1. INTRODUCTION
Consumers are interested with automated classification of food grains and high expectation about the purity of the food grains. Food grains therefore, have to be cleaned and prepared to make suitable for consumption. The food industry is expensively investing to ensure a high product quality. Unfortunately, even after processing, some contamination will always occur.

To overcome this problem the food industry is investigating in all fields of purity control. This paper refers to the classification of bulk food grain samples and identification of foreign bodies among food grains. A foreign body is defined as a piece of solid matter present in the product that is undesirable. The food manufacturer's objective is to supply food grains free from foreign bodies to meet the consumer expectations.

The decision-making capabilities of human-inspectors are being affected by external influences such as fatigue, vengeance, bias etc. Hence, development of a Machine Vision Systems (MVS) becomes essential as an alternative to this manual practice in the context of current technological era so as to enable to overcome the aforesaid influences.

Identification of Basmati Rice grain of India and Its Quality Using Pattern Classification (Harish S Gujjar et al, 2013). The effect of foreign bodies on recognition and classification of food grains is given In(B.S Anami et al. 2009). Geometrical and color features such as size, shape, RGB etc., are extracted. A neural network model is developed for classification. (Anami B.S et al, 2009) have developed a knowledge based nearest mean classifier for classification of Bulk Food objects. Machine vision systems are successfully used for recognition of greenhouse cucumber using computer vision (Libin Zhang et.al ,2007). A method for the classification and gradation of different grains (for a single grain kernel) such as groundnut, bengal gram, wheat etc, is described in(B.S Anami et al. 2003). Some researchers have used an artificial neural network approach to the color grading of apples(Kazuhiro Nakano1997).

A novel method for segmentation of apple from Video via Background Modeling is carried out by (Amy L. Tabb, et.al 2006). A Robust algorithm for segmentation of food images from a background is presented by (Domingo Mery and Franco Pedreschi ,2008). A high spatial resolution hyper spectral imaging system is presented as a tool for selecting better multispectral methods to detect defective and contaminated food and agricultural products is given by (Patrick M. Mehl et.al. 2004). Some have developed a machine vision system for automatic grading of Mushrooms (P. H Heinemann, et.al, 1994).

An artificial neural network approach is used to identify and classify the bulk grain samples (McCollum et.al, 2004, B.S Anami et al. 2008, 2006; Kivanc Kilic et al.2006). They have illustrated the application in category identification tasks of three different kinds of image data. (Giaime Ginesu et al, 2004) have worked on detection of foreign bodies in food by thermal image processing. (D. Patel et al, 2004) have described a monitoring system, which detects contaminants such as pieces of stone or fragments of glass in foodstuffs.

In this work images of different grains are obtained using camera, the color and textural features are extracted using image processing techniques. These features are used to train the BPNN model. The developed neural network model is tested for classification of different grains as pure and impure. After classification the impure grain image sample is processed to detect foreign body, its location and its category using segmentation by threshold. The work carried out involved image processing, pattern recognition and neural network technique.

The proposed work emphasizes on development of ANN model for automatic recognition and classification of bulk grain samples and image segmentation method for detection of foreign body, its location and its category in impure grain sample. The block diagram represents the different phases involved in the work shown in figure 2.

## 2. COLOR FEATURE EXTRACTION

Color is usually based on Red, Green and Blue (RGB) primary color system. From the original images shown in figure 1, RGB components are separated and the HSI components are derived. The components RGB and HSI are of size M * N. The mean, variance and range of all these 6 components are calculated using the standard feature extraction algorithm and a total of 18 color features are stored in color database. The database consists of simple flat files.

### 2.1 Sample Images

**P bengal gram1 p bengal gram2 ip bengal gram1**

**P Chennangi1 P Chennangi2 iP Chennangi1**

**P Red Gram1 P Red Gram2 iP Red Gram**

**P Ground nut1 P Ground nut2 iP Ground nut1**

**P Green gram1 P Green gram1 iP Green gram1**

**Legend : P: Pure ip = impure**

**Figure 1: Images of Food Grains sample**

## 3. TEXTURAL FETURES EXTRACTED FROM GLCM

Texture is a connected set of pixels that occur repeatedly in an image. Texture is one of the important characteristics used in identifying the object or regions of interest in an image. It provides the information about the variations in the intensity of a surface by quantifying properties such as smoothness, coarseness and regularity. GLCM mean, energy, variance, range, contrast, correlation, homogeneity etc. for three color components RGB are calculated using the standard texture feature extraction algorithm. The GLCM method of texture description is based on the repeated occurrence of some gray-level configuration in the texture.

## 4. PROPOSED NEURAL NETWORK MODEL

Multi-layer feed-forward neural networks are the most commonly used neural networks for object classification. The number of nodes in the hidden layer is calculated using the formula

$$n = \frac{I + O}{2} + Y^{0.5}$$

Where ,n = number of nodes in hidden layer, I = number of input features, O = number of outputs and Y = number of input patterns in the training set.

The BPNN model used for first level classification (grain type) is shown in figure 3. A similar model with only two output nodes is used for second level classification (pure/impure type). these designed networks are trained using algorithm 1

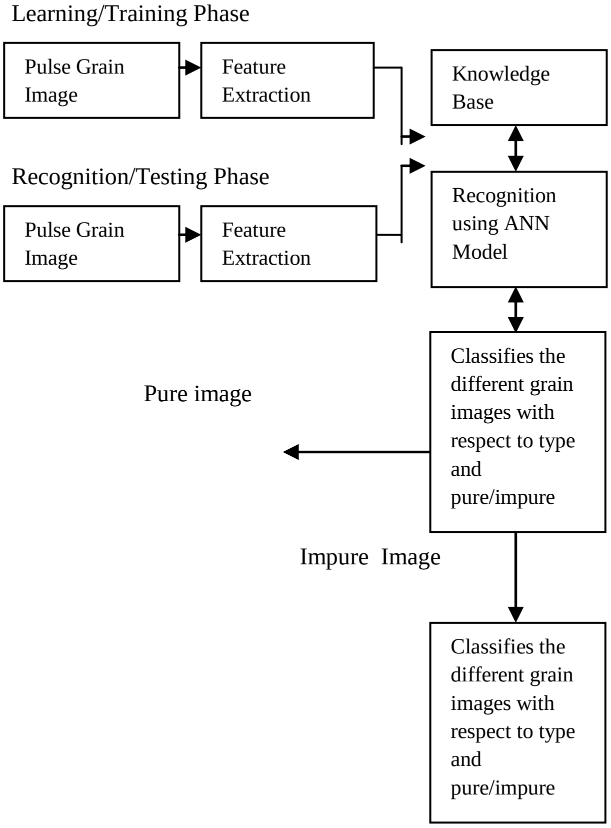


**Figure 2: Proposed method for classification of grains and detection of foreign bodies.**

**Step 1**: Initialize the weights in the network (randomly).
**Step 2**: **Repeat**
For each example e in the training set do
    Forward pass
    **0** = Actual neural net output for e;
    **T** = Desired output (Target) for e;
    Calculate error (**T – O**) at the output units;
**Backward Pass**
Compute delta_wi (Change in weight) for all weights from hidden layer to output layer;

Compute delta_wi for all weights from input layer to Hidden layer;
Update the weights in the network;
**End**
**Until** all examples classified correctly or stopping criterion satisfied.
**Return** (network)
**Stop.**

**Algorithm 1: Back-propagation Learning.**

The output for network for grain type classification is represented by five neurons discriminating between the classes. Each neuron is associated with one class. For example, the following resultant vector means class3 (Red gram) Output = [0 0 1 0 0]. Similarly for pure/impure classification, the output network is represented by two neurons discriminating between the classes. For example, the following resultant vector means class2 (Impure) Output = [0, 1].

## 5. FOREIGN BODY DETECTION METHODOLOGY

In this method, the impure images is taken and it is pre-processed. Then the segmentation is applied to the pre-processed image to obtain the output image indicating the foreign bodies. For the segmented image two binary images are obtained to find the count, location and type of foreign bodies. Proposed model for foreign body detection shown in figure 3.

**Input**: Original 24-bit color image
**Output:** Image showing foreign body.
**Start**
**Step 1**: Read the input image.
**Step 2**: Preprocess the input image.
**Step 3**: For all pixels($x_1$, $y_1$) in the image do
If image (i, j) >= T2 then image (i, j) = 1
If (image (i, j) < T2 && image (i, j) >= T1)
Then image (i, j) = 0.5.
Otherwise set image (i, j) = 0
**Step 4**: Show the resulting image.
**Stop.**

**Algorithm 2: Detection of foreign body in given image.**

**Input**: Image highlighting the foreign body.
**Output**: Location, type and count of foreign bodies.
**Start**
**Step 1**: Take the image containing foreign body.
**Step 2**: Apply binarization to obtain two different images.
**Step 3**: Calculate number of foreign bodies in each image separately.
**Step 4**: For each foreign body
a. Find the position.
b. Find the category.
**Step 5**: Apply same background to both images.
**Step 6**: Add the two images to obtain single image with all foreign bodies.
**Stop.**

**Algorithm 3: Find position, type and count of foreign bodies.**

Algorithms 2 and 3 are applied to original image after pre-processing sequentially, figure 3 shows the result of applying algorithm 2 to one of the impure chennangi sample. Finally algorithm 3 is used to find location, count and type of foreign bodies and results are displayed on the screen.

## 6. RESULT AND DISCUSSION

The developed models has been tested for known and unknown samples for grain type and pure/impure type classification using three different features sets viz., color, texture and combination of both. The observed classification and detection accuracies for all considered grains are about 85% and 83% respectively. In this paper the grain type classification results for known and unknown samples using only texture features are given. Detection accuracy and recognition/misrecognition results are discussed below.

### 6.1. Grain Type Classification Result

A BPNN classifier (feed-forward 45-37-37-5) is developed to classify the grains with respect to their type using combined features.

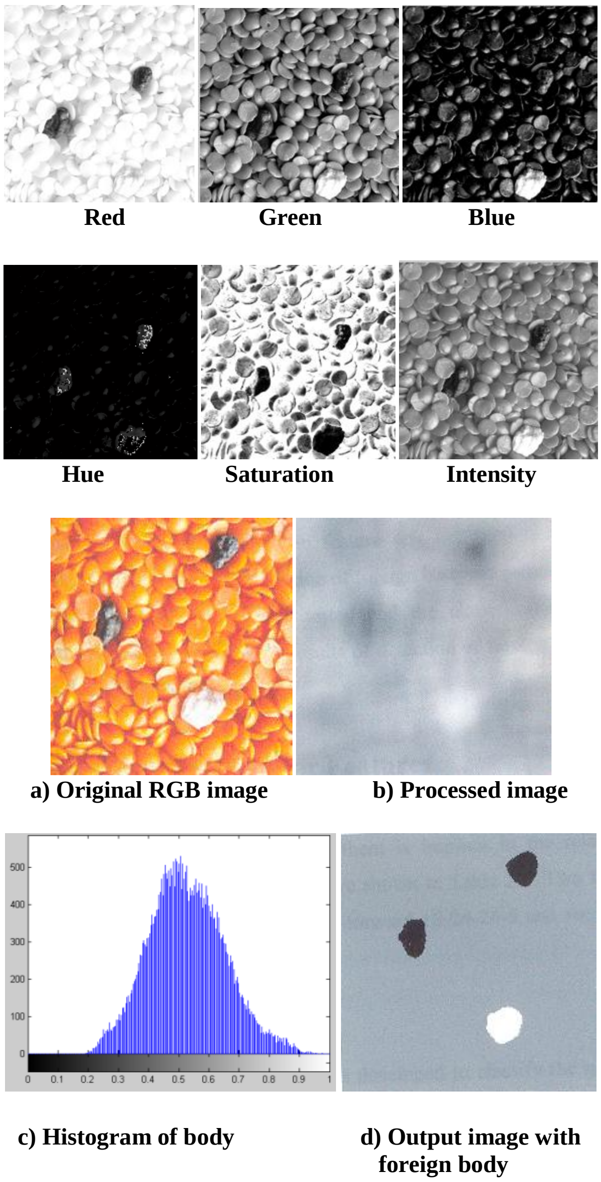


**Figure 3: RGB and HSI components extracted and Result of applying algorithm 2 to one of the impure chennagi sample.**

Using this developed BPNN model several images of known and unknown samples are tested and classification accuracies are as given in Table 1 and Table 2 for known and unknown samples respectively. The developed network grains has classified the grains with 100% accuracy for known samples and the model has resulted with minimum of 80% accuracy and maximum of 100% accuracy for unknown samples using texture features.

**Table 1: Grain Type Classification Accuracy for known Samples Using Texture Features.**

| Sl. No. | Category of Grains | Classification Accuracy | Remarks |
|---|---|---|---|
| 1 | G1 | 100% | |
| 2 | G2 | 90% | 1 sample of G2 misclassified as G3 |
| 3 | G3 | 100% | |
| 4 | G4 | 100% | |
| 5 | G5 | 100% | |

Legend: G1: Bengal Gram G2: Chennangi
G3: Red Gram G4: Groundnut
G5: Green Gram

## 6.2. Result of Foreign Body Detection

For the evaluation of this method, six different test images of each grain category which are acquired with a color camera (DXC – 3000A, Sony Tokyo Japan) in an experimental environment are used. This method shows the correct result for five test images of Bengal Gram and incorrect result for one image of Bengal Gram (83% accuracy). The detection accuracy for all the different types of grains is as tabulated in Table 3. This method detected for foreign bodies in test images with accuracy of 83% for G1, G3, G4 and G5 and accuracy of 100% for G2 (Chennangi).

The foreign body recognition result is evaluated using the ratio between recognized and misrecognized foreign bodies, where recognized means foreign bodies present in the original data, and misrecognized means food objects recognized as foreign bodies. The recognition and misrecognition results are shown in the Table 4.

**Table 2: Grain Type Classification Accuracy for unknown Samples Using Texture Features.**

| Sl. No. | Category of Grains | Classification Accuracy | Remarks |
|---|---|---|---|
| 1 | G1 | 80% | 1 sample of G1 is misclassified as G4 |
| 2 | G2 | 100% | |
| 3 | G3 | 100% | |
| 4 | G4 | 100% | |
| 5 | G5 | 80% | 1 sample of G5 is misclassified as G3 |

**Table 3: Foreign Body Detection Accuracy for Five Categories of Grains.**

| Sl. No. | Category of Grains | Detection Accuracy | Remarks |
|---|---|---|---|
| 1 | G1 | 83% | |
| 2 | G2 | 100% | For 1 Sample of G2 3 Foreign Bodies are detected instead of 2. |
| 3 | G3 | 83% | In 1 sample of G3 4 Foreign Bodies are detected instead of 3 |
| 4 | G4 | 83% | In 1 sample of G3 4 Foreign Bodies are detected instead of 2 |
| 5 | G5 | 83% | In 1 sample of G3 2 Foreign Bodies are detected instead of 1 |

**Table 4: Test Result on Recognition and Misrecognition of Foreign body.**

| Sl. No. | Sample Name | Actual No. of Foreign Body | | Recognized No. of Foreign Body | | Count of misrecognised Foreign Body |
|---|---|---|---|---|---|---|
| | | W | B | W | B | |
| 1 | 1 sample of G1 | 0 | 2 | 0 | 2 | 0 |
| 2 | 1 sample of G2 | 2 | 1 | 2 | 1 | 0 |
| 3 | 1 sample of G3 | 2 | 2 | 3 | 2 | 1 |
| 4 | 1 sample of G4 | 1 | 1 | 2 | 2 | 2 |
| 5 | 1 sample of G5 | 1 | 1 | 1 | 1 | 0 |

Legend : W: White B: Black

## 7. CONCLUSION

The results obtained confirm that a properly trained ANN model is ideally for real time grain classification and well planned detection method is able for detecting the foreign bodies, which requires very fast execution times. Therefore, it is concluded that an ANN based grain classification foreign detection system has potential usage in Agricultural/Horticultural sciences, APMC yard, Food industries etc.

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