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Product defect categorization using machine vision through machine learning

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Product defect categorization using machine vision through machine learning

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Abstract. O-rings are among the seals most often used in the industry. O-rings accuracy measurement and inspection play a significant role in seal quality control. Human tests can be unpredictable and can take time. The goal of this paper is to use detection algorithms based on machine vision technology to monitor the O-rings norm, which also has the correct measurement rule and the classification rule. During this, we find an entirely different variety of good defects, Material shortage, Bounce, Spiral, and Breakage. Extract values for the elements by using MATLAB. Feature selection optimization attribute choice with MATLAB and classification exploitation of KNN, SVM, call Trees and alternative classifier variety with MATLAB is performed to check for the utmost prediction precision. To evaluate the recorded images of O-rings and conduct the measurement and inspection processes a computer vision program is applied. Then the GUI system is built to interface the user with the credibility of accessing the trained model. The proposed GUI is tested via a sequence of O-rings being checked.

Keywords— Machine vision, machine learning, kNN, SVM, GUI.

1. Introduction

Consistency of sealing is an important characteristic for deciding the uniformity of the unit. Consistency of sealing will impact directly on system accuracy and stability. O-ring is currently the most widely used standardized, simple sealing feature. So, ensuring the consistency of the O-rings is especially important. The detection of O-rings is generally dependent on human scrutiny. Most professional inspectors identify O-rings in the appropriate lighting conditions, poor accuracy, high amount of labor, and sometimes time-consuming. It is also uncertain, as the outcomes of experiments are vulnerable to qualitative variables. Hence, good quality is hard to guarantee. Computer vision is a good tool for identifying a variety of faults occurring in the o ring. Then, according to Guoliang Peng et al.,[1] it's possible to study different types of defects in the O ring. An analysis is performed to classify six metal surface groups with varying degrees of roughness. Tree classifier has given very successful results by Hon-son don et al.,[2] Type of Camera to be selected for the experiments can be identified from the learning of Cheng-Jin Du et al., [3] Algorithms like CKFD(complete kernel fisher discrimination) are used by Jian Yang et al.,[4]which describes the requirement of the various

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algorithm the image processing requires. Our project mainly depends on the pixel data of the image acquired. The key to successfully detect the pixel data and to extract the features using the pixel data has been explained by G.E. Meyer et al., [5]. The usage of software like Matlab in image processing is dealt with by LI Lin WANG et al.,[6] and it has been explained the importance of various software required for the image processing techniques. The defect classification of basic defects in very cheap materials are carried out by the human vision which has very low efficiency and precision is explained by H. Shen, S. Li, D. Gu, et al., [7]the extraction of data from the pixel value for the fire detection is explained by Tom Toulouse[8] from which we can understand the pixel data extraction. Thus, to have a machine learning approach with machine vision data various classifiers are to be used trial and error basis to have the most accurate results.
Machine learning has become one of the essential tools in the intelligent manufacturing system which helps to predict failures and helps in reducing rejections. The fault diagnosis of the manufacturing system is currently becoming the key research in intelligent or smart manufacturing for predicting the failure with very high accuracy. For this highly sensitive image processing manufacturing system like product defect categorization requires machine learning techniques to avoid the rejections. After feature extraction is feature selection which is one of the important processes in the machine learning approach. Then comes the feature classification, in which the decision tree algorithm has better accuracy compared to other algorithms. Cubical SVM and also ensemble bagged trees algorithm has better accuracy. Thus, in the application of defect categorization, the image processing technique can be predicted by pixel data.

2. Methodology

The methodology for Product defect categorization using machine vision through machine learning is as shown in the Fig.1. The process starts with the acquisition of the image. The image after acquiring is then converted into the required statistical data from the pixel data of each image. The data is then used for further classification using the classification learner tool in Matlab.

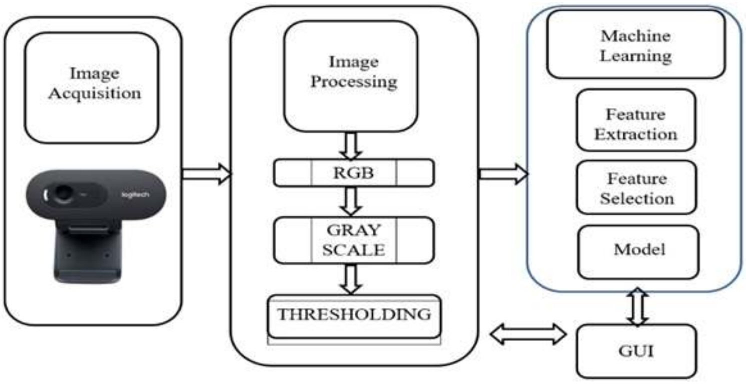

Figure 1. Methodology

3. Machine learning approach

Machine Learning is the way to construct an inductive show that learns from a constrained sum of information without the requirement of specialists. The Machine Learning models predict an overseen learning figure with marked information output and unattended training draws deduction from subtle elements without named inputs. For administered learning, we recognize between models that foresee a numeric variable or a categorical variable. Model learning implies that a model's parameters can be fitted to a specific dataset and upgraded iteratively through a few information passes until a specific predefined work has been minimized.

3.1. Feature Extraction

The feature extraction is one of the key steps in machine learning [9]. The information gotten from the information procurement is extracted as measurable strategies like mean, standard deviation, variance, kurtosis, skewness, root mean square, etc [10]. The images of O-rings were taken in numerous introductions under distinctive blame conditions utilizing Matlab and the pixel values were extricated by changing the color of the picture to gey scale the total pixel information has been extracted as features.

3.2. Feature Classification

Feature classification helps in classifying the data for different fault conditions using different classification algorithms. The different classification algorithm such as kNN, bagged tree, SVM, tree family classifiers has been used in this study.

3.2.1. Decision tree algorithm. The decision tree procedure is utilized for the classification by tree-structured calculations of information into isolated shapes. This decision tree's essential reason is to illustrate the structures of the information. This standard tree comprises of root hub, leaves, hubs, and a few branches, Include vectors are categorized from the root to the hub of the leaf developing choice tree. In each division hub within the tree, the foremost valuable include based on the estimation criteria can be chosen. Decision tree calculation has a place in the family of supervised learning calculations. The decision tree calculation tries to unravel the issue, by utilizing tree representation [11].

3.2.2. kNN (k-Nearest Neighbour). KNN is a type of supervised algorithm for machine learning which is used for classification and regression problems. This is used mainly in manufacturing, through problems of statistical classification. K-NN is a lazy learner since it does not learn from the training data about a discriminative function but rather memorizes the training data package. For machine learning, we get confused with K and KNN K means clustering that uses the problem of clustering and it is a learning that is not supervised. Where KNN means (K- Nearest Neighbour), which means that learning is supervised and used for problems of classification and regression [12].

3.2.3. SVM (Support Vector Machine). SVM is another type of algorithm used in machine learning. The purpose of SVM is to locate hyperplane in an N-dimensional space that categorizes data points. SVM is another type of machine learning algorithm / SVM's aim is to find a hyperplane in an N-dimensional space that classifies data points distinctly. SVM can produce good accuracy with less power of consumption it will be used for problems of regression and classification. Help vectors are data points closer to the hyperplane, which influence the hyperplane's direction which orientation. If we remove the SVM this will shift the hyperplane position [13].

3.2.4. Bagged trees classifier. Bagging has one parameter, that is, the number of trees. All trees area unit grown binary tree (unpruned) and searches for all options at each node within the tree to find the function that best separates the information at that node. The fundamental difference is that only a subset of features is randomly selected from the total in Random Forests, and the best split feature from the subset is used to split each node into a tree, unlike in bagging where all features are considered for splitting a node [14].

4. Statistical features

The selection of features in machine learning and statistics, also referred to as variable selection, is the method of selecting a subset of features that are appropriate for use in model construction. Yet again, feature selection retains a subset of the unique features while feature extraction produces new ones [15]. Here we use various types of statistical properties, such as mean, skewness, kurtosis, square root mean, standard deviation (SD), and variance.

4.1. Mean
The statistical mean refers to the average or mean used to assess the central trend of the data in question. It is determined by adding all data points of a population and then dividing the sum by point number. The resulting number is known as the mean or average. The cumulative mean is numbers. It is easy to calculate: add all the numbers, then divide by how many numbers there are.

4.2. Skewness
Skewness in probability theory and statistics is a measure of the asymmetry of the probability distribution of a real-valued random variable about its mean. The skewness value can be positive, negative, null, or unknown. Negative skew for unimodal distribution usually means that the tail on the left side of the distribution and positive skew implies that the tail is on the right side.

4.3. Kurtosis
Kurtosis in either tail tests the extreme values. Wide kurtosis distributions show tail data that exceeds the normal distribution tails (e.g., five or more standard deviations from the mean). Low kurtosis distributions exhibit tail data which is usually less extreme than normal distribution tails. Sometimes the kurtosis is confused with a measure of a distribution's peakedness. Kurtosis, however, is a metric that defines the shape of the tails of distribution as opposed to its overall form. With low kurtosis, a distribution can be infinitely capped, and distribution with infinite kurtosis can be perfectly flat-topped. It tests "tailability" and not "peakedness"

4.4. Standard Deviation
In mathematics, the standard deviation is a function of how much isolated or distributed a set of values are. A low standard deviation means the values tend to be identical to the fixed mean whereas a high standard deviation means the values are spread over a broader range. The primary and most important purpose of standard deviation is to understand how a data set is spread out. When you imagine a cloud of data points, you will be given the 'normal' value of a data point in that cloud by drawing a line through the center of it

4.5. RMS value
The root mean square (RMS) is defined as the square root of the mean square (the numerical mean of the squares of a series of numbers). The RMS is also known as the quadratic mean and is a special case of the generalized mean with exponent RMS for a continuously variable function in terms of an integral of the squares of the instantaneous values during a phase

4.6. Variance
Data scientists use variance as a statistical method to better understand the distribution of a data set. Machine learning uses variance calculations to generalize a data set, helping to explain the distribution of data in a neural network. Variance is also used with distributions of probability

5. Fault conditions
There are five common O-rings defects, such as Material Shortage, Fine, Bounce, Breakage, and Spiral. An O-ring's premature breakdown in operation can typically be due to a variety of factors, and not just a single breakdown mode. We can distinguish the product with different faults by using the image processing technique.

5.1. Material Shortage
Many faults in the O-ring may be specifically ascribed to inadequate deployment. The O-ring is a precision tool that needs care during installation, despite its simple look. Some of the more common causes of O-ring failure due to sloppy handling are listed in the following

1. Oversize O-ring on piston seal application.

2. Undersize O-ring on rod application.
3. O-ring twisted/pinched during installation.
4. O-ring not properly lubricated before installation.

Figure 2. Material Shortage

5.2. Spiral Failure
The seal exhibits a faint spiraling pattern around its edge, with the subsequent deep cutting of the seal surface at angles of 45 degrees where the highest levels of stress are evident. An O-ring can spiral during active, reciprocating motion, either during installation or during use. There are many different factors influencing the spiralling progression, such, but not limited to, uneven surface finishes, inadequate lubrication, friction, defects in construction, and eccentric parts. This fault will lead to the leakage of the fluid in the suspension causing the sag and sometimes complete failure of the entire unit. Hence it has to be checked predominantly before its inscription into the shock absorber.

Figure 3. Spiral Failure

5.3. Bump
A pocketed bulge on the top of the O-ring resembling a bubble of air. Blisters in a part resulting from the incomplete removal of rubber air during manufacturing, while the remaining air was trapped in the O-ring during the process of curing. If you stretch the O-ring, this will make the defect more pronounced.

Figure 4. Bump

5.4. Good
This is the one which is having no defects in that O-ring

Figure 5. Good

5.5. Breakage

Breakage may occur due to insufficient (or inadequate) lubrication and even if the O-ring is too soft. When installing it if we are not properly configured (or) unsuitable installation Breakage will result in serious damages

Figure 6. Breakage

6. Results and discussion

Classification of images performed using MATLAB's classification learner method. The data is obtained from the processing of images. After the picture has been acquired the classification of the element and the extraction is completed. The aforementioned statistical data is extracted from each image and the data is then compiled. Classification with this method is performed with different classification algorithms using the collected data.

6.1. Classification Accuracy

The extracted data were classified using the various algorithm namely Quadratic Discriminant, complex tree, SVM, kNN, and Decision tree. The corresponding accuracies were given in Table 1.

Table 1. A simple table indicating the accuracy of various algorithms

S.No	***Algorithm***	***Classification Accuracy (%)***
1	Quadratic Discriminant	56.8
2	Complex Tree	77.4
3	Cubic SVM	84.7
4	Fine KNN	84.5
5	**Bagged Trees**	**88.7**
6	Decision Tree	78.72

6.2. Confusion Matrix

6.2.1. Quadratic Discriminant. In this experiment, it is shown that for the five fault conditions, Quadratic Discriminant has a minimum accuracy of 56.8 percent. From this Quadratic Discriminant

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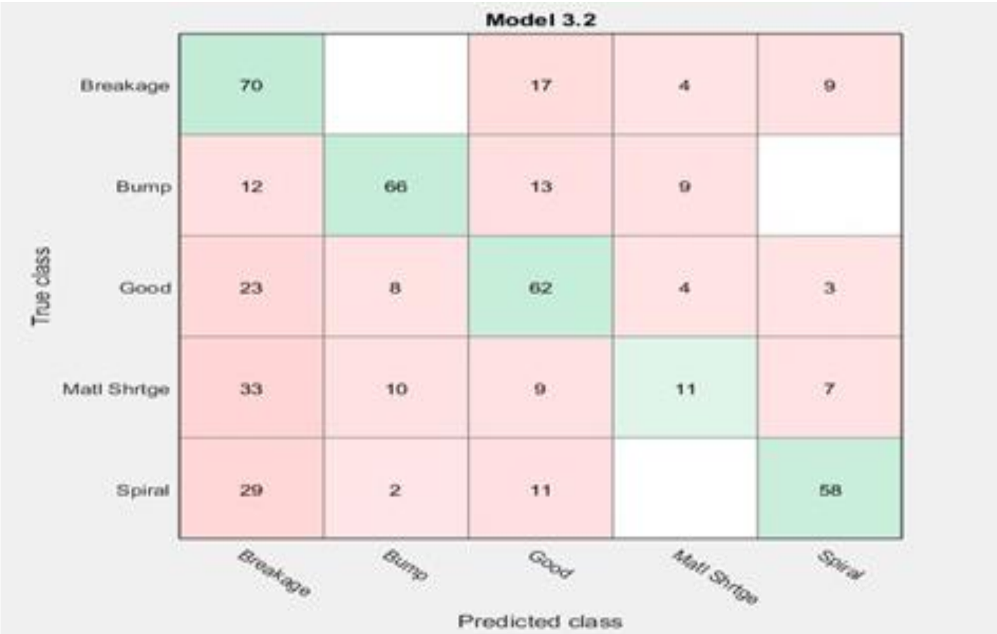
uncertainty matrix, we can see that data is correctly predicted and data is erroneously predicted for all five conditions, the diagonal elements are the data that is predicted as accurate. We take 100 sample data to predict breakage of 70 items and the remaining 30 items are mispredicted as good, material shortage, and spiral.



.**Figure 7.** Quadratic Discriminant

6.2.2. Complex Tree: The confusion matrix for the complex tree has been shown in Figure 8.n The overall classification accuracy is found to be 77.4 %.

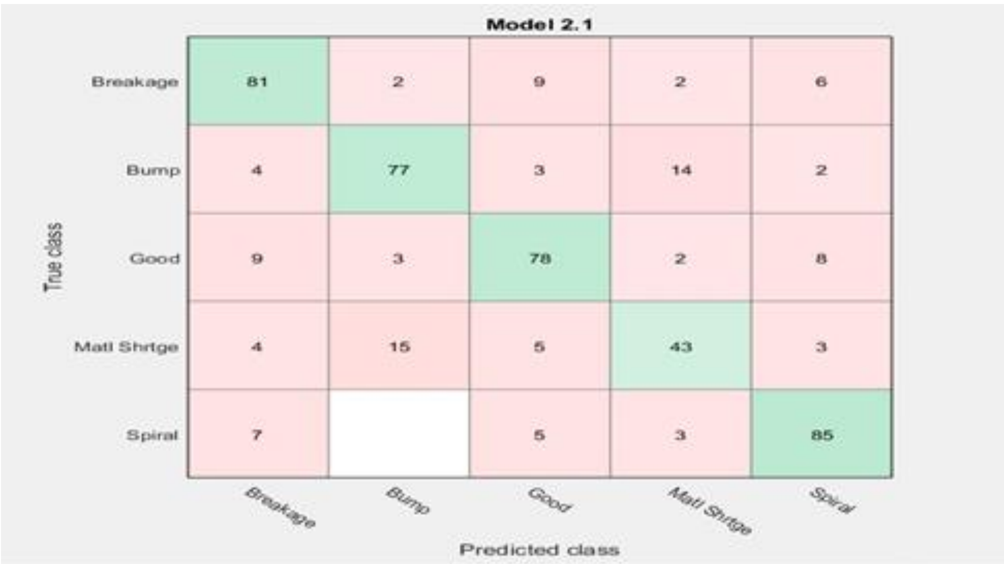


Figure 8. Complex Tree

6.2.3. Cubic SVM: The confusion matrix for the Cubic SVM has been shown in Figure 9. The overall classification accuracy is found to be 84.7 %.

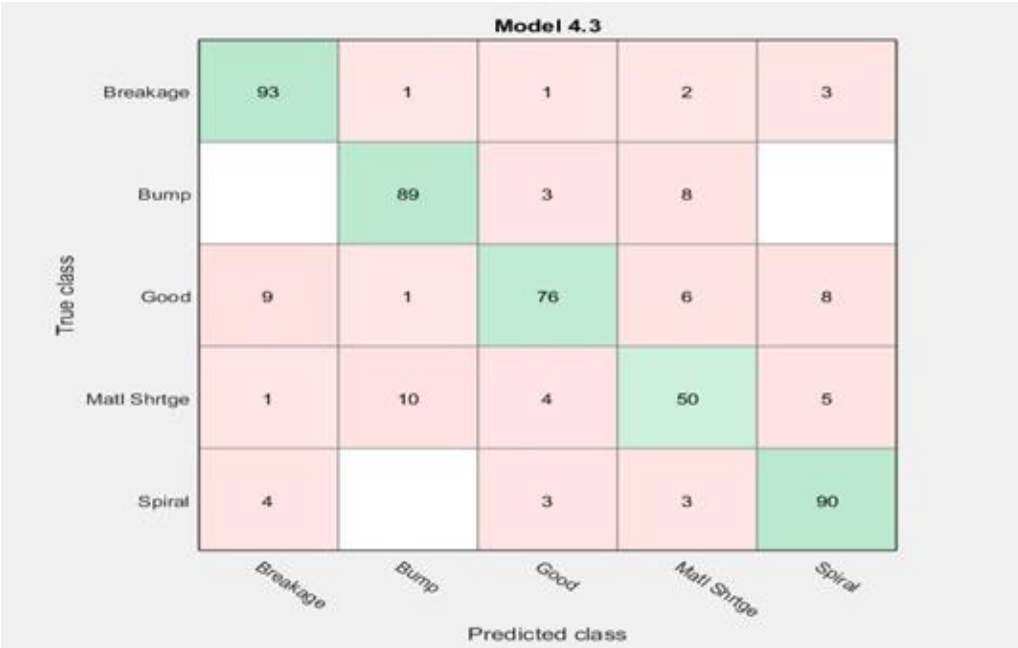


Figure 9. Cubic SVM

6.2.4. Fine KNN: Figure 10 shows the confusion matrix of the kNN algorithm for the fault classification and it produced a maximum accuracy of 84.5 %.

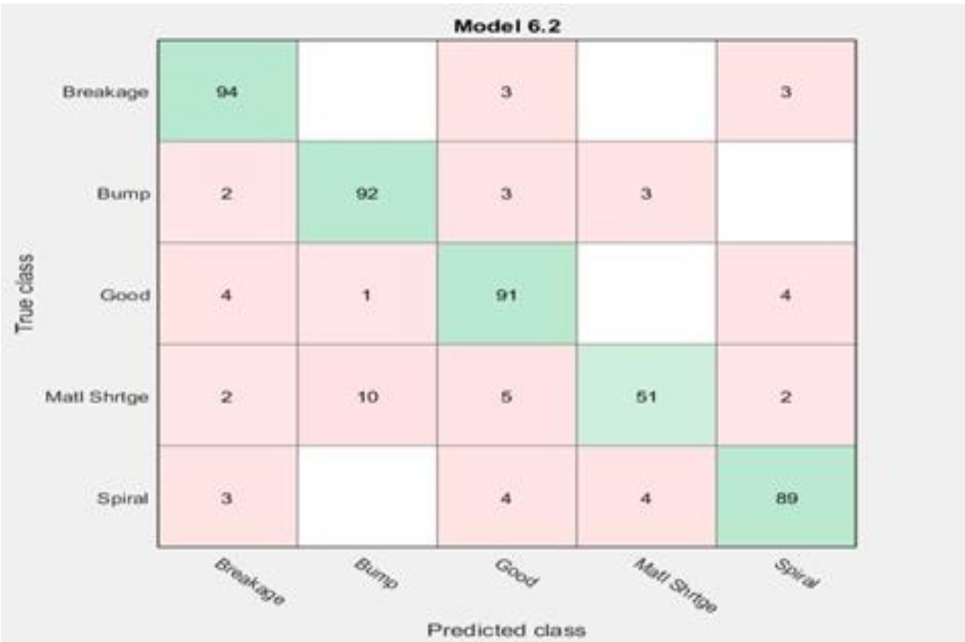


Figure 10. Fine KNN

6.2.5. Bagged Trees. From the confusion matrix, the highest accuracy is obtained from the bagged tree algorithm (Figure 11). It has an accuracy of 88.7 % for the five fault conditions. When considered from the other algorithms it is used for the classification purpose in this study. The confusion matrix indicates the misalignment of the data is more with the material shortage data. It is mainly the cause of the reduction in the entire accuracy rate of the model.

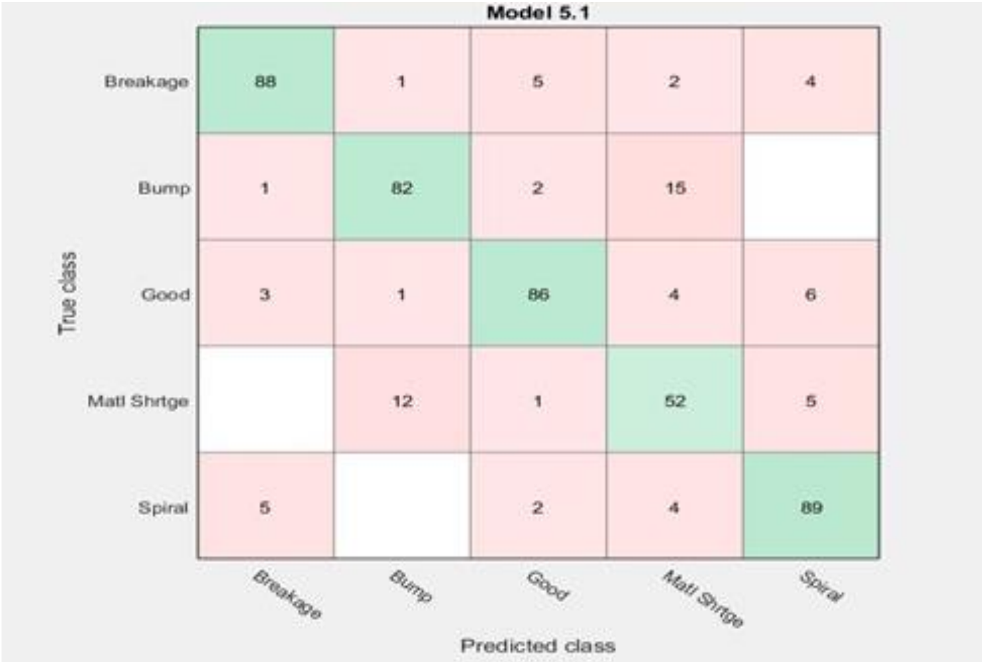


Figure 11. Bagged Trees

7. Graphical user interface

The graphical user interface was developed using the GUIDE tool in Matlab. GUIDE is one of the easiest-to-use software to build the Interface. The results obtained from the classification learner were converted to m-code, and this code is then inscribed in the code. An Interface model for basic image processing techniques and the essential classification component has been developed. Basic conversions and masks such as sobel, prewitt, etc can also be easily realized with this interface. The Graphical User Interface (GUI) has the features to extract the required features. The inscribed bagged tree model will be used for the image classification. The developed GUI was successfully tested with the sample images extracted from the acquired images.

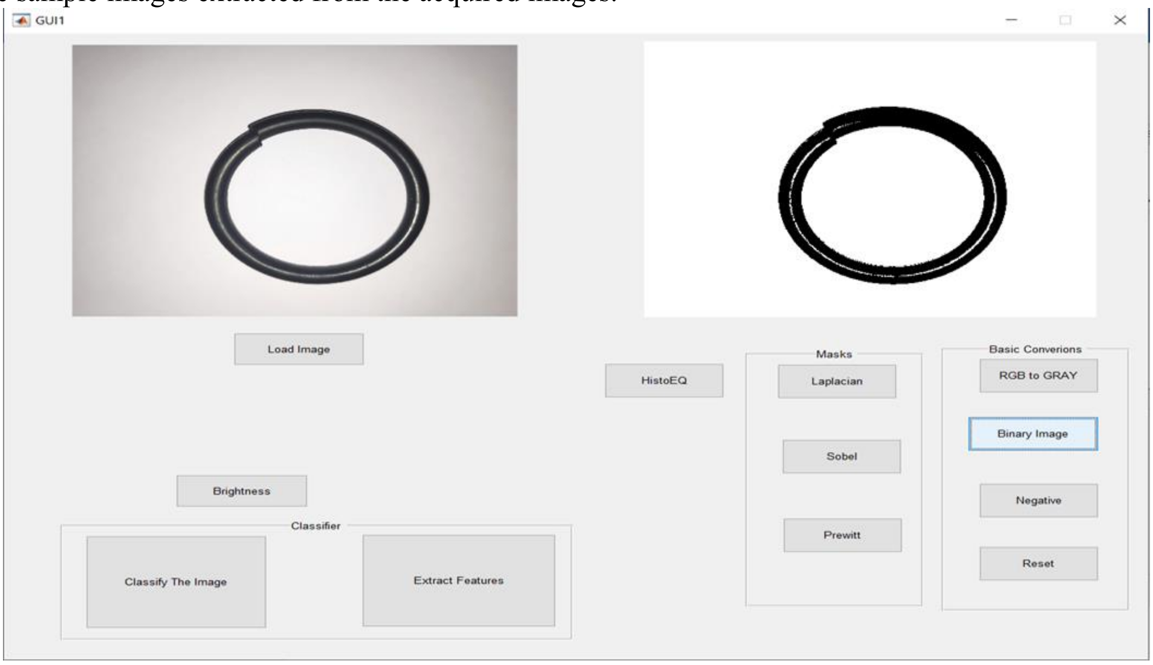


Figure 12. Graphical User Interface (GUI)

8. Conclusion

In this research, the O-rings defect analysis is performed using the techniques of machine learning. Although the O-rings are considered a cheap product in industries, the damage caused by unsuitable O-rings may create a major loss for industries where they are highly dependent on sealing their products, particularly the shock absorbers. The shock absorbers can ultimately particularly the air shock absorbers, without proper sealing. So, machine learning is carried out to identify the defects of these O rings. The mathematical functions are learned and used for machine learning. We acquired an accuracy rate of 88.7 percent using machine learning algorithms such as bagged trees. In the case of more image processing and more data, the accuracy will be greatly improved. Then we developed the Interface using the above algorithm where we can perform basic image processing techniques and ultimately classify the image using the trained model obtained from the learner in the classification. Using deep learning techniques such as CNN will increase accuracy.

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