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A Technique for Glass Defect Detection

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Abstract:
Glass is a material which is used in the industry and household. The presence of defects or weaknesses in the glass has serious implications. In a glass substrate, the grey level of defects and background are hardly distinguishable and results in a low contrast image. The primary objective of this paper is to develop a method for detection of defects in a glass surface image such as subtle defect , bubble defect , dirt defect checks or marks defect etc. The paper proposes artificial neural network based methodology to detect the defects in the glass Gray level Concurrence Matrix (GLCM) has been used for feature extraction. The neural network is responsible for making intelligent classification based on observations done for various types of glass defects. Experimental results developed a classification matrix and by which performance goal based on MSE (mean square error) is set. .This technique helps to get better results.

Key words: *GLCM, ANN, MSE, defect detection, image Processing*

1. Introduction

The glass can be used in different field as decorative art, housing, furniture, factories, light bulbs and its translucent quality is desirable in many situations because it provides privacy where the full transparency of the glass is undesirable [1]. Glass defect is a major problem for poor quality in a glass which is a reason of embarrassment for glass manufacturing industries. The manual inspection process is slow, time-consuming and prone to human error [1]. Surface inspection is one of the most important part of quality control in manufacturing. In recent years, image analysis techniques have been increasingly used in industries for surface defect inspection, whereas one has to detect small defects that appear as local anomalies in material surfaces [2]. The various types of defects that can be present in the glass are:

- **Checks**: This type of defect consists of miniature and slight crack which does not cause leakage but it certainly weakens the body wall.
- **Non-glass inclusions**: Glass defect due to dirt, adhering to any unsustainable particles or due to enormous oil parks.
- **Marks**: Marks depict the spot or any stray marks in the glass which diminishes the quality of glass. The body of the glass becomes thinner and weaker.

Few researchers have studied the defect detection in glass images.

Ghorai et al. [3] Developed an automatic defect detection method on hot–rolled steel surface. This method is focused to derive a set of good-quality defect descriptors from the surface images and is used to evaluate a performance by a number of different wavelet feature sets such as: Haar, Daubechies 2 (DB2), biorthogonal spline and multiwavelet in different decomposition levels derived from 32*32 contiguous (no overlapping) pixel blocks of steel surface images.

Shin-Min Chao [4] focused on defect detection on low contrast images. This method utilized anisotropic diffusion model. It defines a diffusion system that was flexible for change in the curve of diffusion co-efficient function. It performed smooth procedure for area without fault and sharpened the defected area of the image.

Hongxi Zhang [5] proposed an algorithm for detection of defect which was based on Discrete Fourier Transformation (DFT). It also demonstrated and implemented the optimal threshold method to detect cracks, bubble and stone in the glass. This algorithm not only detects but also localized the region of defect.

The above methods discussed that the defected region of lower or less contrast image could be determined by various methods. In the sensed image of a glass substrate, the gray level of defects and background are hardly distinguishable and result in a low-contrast image [2]. Texture analysis techniques are used to detect the defects in stretched images rather than the simple thresholding method [5]. It is not easy to positively identify miniature defect of a low contrasted image in the absence of false detection of the noise [6] -[7]. This paper proposes an artificial neural network method to implement the problem of defect detection in low-contrast glass substrate images.

2. The Proposed Technique

Firstly, proposed technique will be checked on the basis of certain parameters such as entropy, contrast, and cluster shade. By implementing this method, it is found that the feature extraction by GLCM (gray level co-occurrence matrices) function gives the best performance. Data Normalization must be used to reduce the number of samples, the complexity of the neural network and the computation time of the neural network.

2.1. Back propagation Training Algorithms

- Levenberg-Marquardt
- Gradient Descent with Momentum
- Gradient Descent

- Levenberg-Marquardt

Back propagation algorithm utilizes the Levenberg-Marquardt algorithm for training of the network. The 'trainlm' is a network training function that updates weight and bias values.

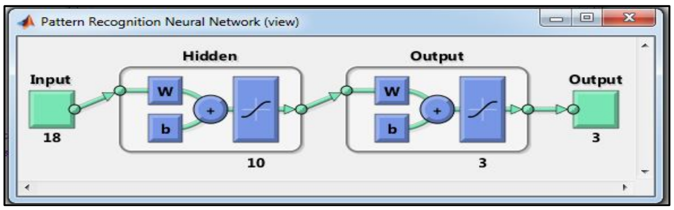

Figure 1: Neural Network Architecture

Figure1 defines the neural network architecture. The neural network is formed by a set of neuron interconnected with each other through the synaptic weights. It is used to acquire knowledge in the learning phase. The number of neurons and synaptic weights can be change according to the desired design. The neural network consists of three layers:

- **Input layer**: The input layer consists of source nodes and it captures the features pattern for the classification.
- **Hidden layer:** This layer lies between input and output layer. The number of hidden layers can be one or more and the hidden nodes can be varying to get the desired performance. The output of this layer is supplied to the next layer.
- **Output layer**: The output layer is the end layer of neural network. It results the output after features is passed through neural network. The set of outputs in output layer decides the response of the neural network for a supplied input features.

Figure 2 shows the basic flow charts that define the defects and non defects in glass images [6]. Dataset in our case is non-stationary as well as non-linear. Neural network is used for understanding the pattern and classifying the glass defects .To maintain the quality control of glass defects detection on surface is important for manufacturing industries [8]-[9]. This provides the information regarding the Quality of glass which is going to be produced.

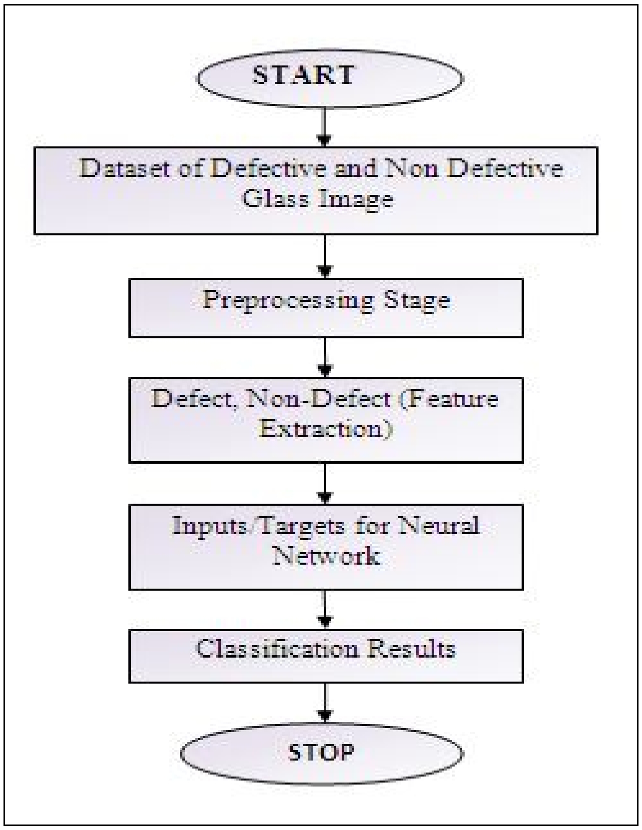

Figure 2: Basic Flow Chart Shows Defect and Non Defects in Glass Images

2.2. The Following Steps Are Involved

- To find the nature of the dataset.
- Algorithm for extraction of color features.
- Algorithm for extraction texture features.
- Selection of classifier for the dataset such as: artificial neural network.
- Normalization of input database.
- Neural network hidden layer number detection.
- Choosing the learning method such as supervised learning.
- Output layer design

The design of output layer depends upon the number of defect types or classes as labeled below:

Target	Defect Class	Target Pattern
Class A	Defect Type 1 ()	1 0 0 0 0 0
Class B	Defect Type 1 ()	0 1 0 0 0 0
Class C	Defect Type 1 ()	0 0 1 0 0 0

Table 1: Number of Defect Types in Glass Image

3. Experiment Results

The proposed work is based on the observations that are taken as color and texture properties of defective and non-defective parts of the glass images. For evaluating system performance and to know the output unit response accuracy, classification matrix is developed and the performance is set based on mean square error.

From the confusion matrix as shown in Figure 3, it can be seen that the lower triangular matrix shows the number of misclassifications while the upper triangular matrix shows the correctly classified glass defects which gets maximum accuracy .

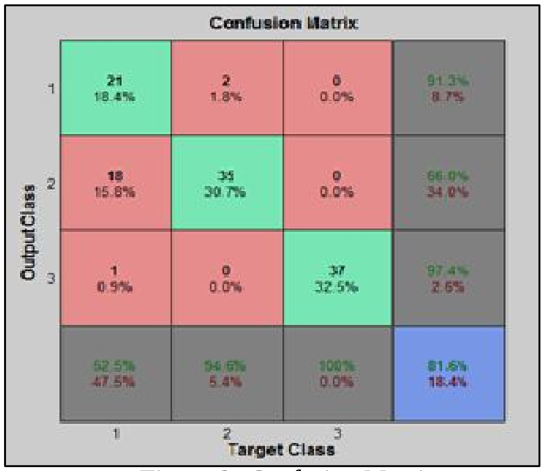

Figure 3: Confusion Matrix

A confusion matrix can be made by using values of true negatives, false positive, false negatives and true positives. These are the standard terms for performance analysis of a classifier. They represent the four different possible outcomes of a single prediction for a two-class case with classes “1” (“yes”) and “0” (“no”).

Mean Squared Error as shown in Figure 4 is the average squared difference between outputs and targets.

$$MSE=\frac{1}{N}\sum_{i=1}^{N}(e_i)^2=\frac{1}{N}\sum_{i=1}^{N}(t_i-a_i)^2$$

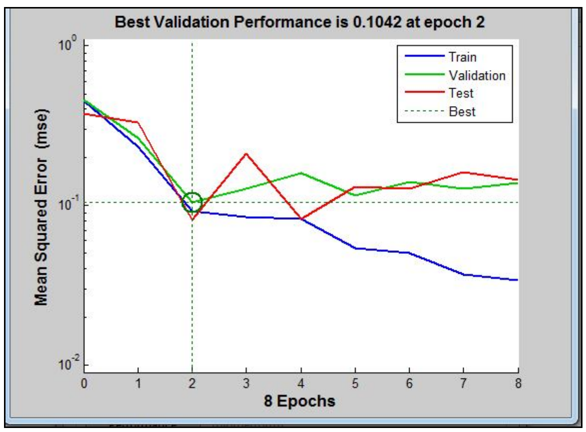

Figure 4: Mean Square Error

Lower values of MSE indicate better performance of the network and zero means no error. Neural network does not need to learn about the glass defects further than eight iterations .So neural network is to run simulation until it reaches the minimum possible mean square error.

4. Conclusion and Discussion

The defect identification is not possible with human eyes or sometimes may be ignored by human. Image processing tools are used to identify the defective glass pieces:-

- It is found that the feature extraction by color and texture feature gives the best performance and more number of features can be extracted by using these methods.
- Data Normalization must be used to reduce the number of samples, complexity and the computation time of the neural network.
- For the classification schemes, it is found that training the model with a large number of test data with fast training algorithm progressively enhance the accuracy and the reliability of the system.
- The design of our classifier is done by running the neural network with different number of hidden layers and it is apparent from the bar graphs that it affects the accuracy.
- It is found that as increasing the number of hidden layers increases the computation time but high order of accuracy is not achieved until it reaches the maximum of hidden layers.

5. Future Work

Unsupervised machine learning algorithms suggests versatile method of identifying various kinds of defects collected by image processing. These methods based on some computational clustering technique and evaluated on the basis of recall and precision values. Work can be extended as:

- Explore more algorithms and techniques for the feature extraction and classification of defects in glass manufacturing process to further improve the accuracy of the defect identification system.
- Improve the system by reducing the complexity. The main objective is to find the best algorithms which optimize the performance and complexity. This can be done by changing normalization of input data or by changing sample methods with other possible learning rate parameters etc.
- The accuracy of classifier can also be enhanced by using more and equal number of training patterns.

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