USE OF ARTIFICIAL INTELLEGENCE IN MECHANICAL MEASUREMENT SYSTEM

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Abstract

Finding errors is the basis or most important work in the production of automatic parts, especially precision parts used in automotive engines. In this article, we made a new proposal to combine relevant information on functional processing with the representational function of deep learning to build a deep-rooted network. Our algorithm includes a deep neural network (DNN) or feature enhancement network divided by pixels. A very complex DNN is proposed to learn the basic properties of part errors. Then, several typical traditional methods used to split the results are converted to complex methods and integrated. We summarize these methods in low networks with fixed weights and empirical thresholds. These thresholds are then released to improve their adaptability and enable end-to-end training. The test results on different datasets show that the method has good portability and is superior to the latest algorithm. Because the contrast of the image is low, it is difficult to detect dents on the hot-rolled steel plate. A periodic defect detection method based on artificial neural network (CNN) and long-term memory (LSTM) is proposed to detect such defects based on the strong temporal properties of periodic defects.

Index Terms—Defect detection, fully convolution ANN, Steel Sheet, SURF.SIFT.

I. INTRODUCTION

Hot sheet steel made of steel is widely used in many technical areas such as ships, bridges, machines, construction and car manufacturing [1]. During the process of fabrication of steel, various types are formed on the surface of the hot iron due to rotational processes such as processing, boundaries, defects, mining, mining, mining opening, and the turning. Defective. These defects greatly affect the appearance and performance of the product, so it is very important to detect the defects on the plate [2]. Currently, the search for deficiencies in media in China employs modern learning methods [3, 4] and convolution neural network (CNN) learning [5, 6].]. This method has high results for long-term deficiencies. For example, Yi Li et al. [7] proposed an end-to-end control system for steel wire. The system uses deep and sensitive neural networks (CNNs) to directly transmit irrelevant images as input and to classify as output. Experiments show that the rate of stroke in the long term is over 96%. In He et al. [8] presented a new target-based measurement system, called Class First Network (CPN) and MG-CNN. In the CPN, picture was first classified by MG-CNN. According to classification results, groups of potentially malicious movie maps are inserted into a neoliberal network based on Yolo (just one note: actual monitoring system) [9] to perform loss control wrong. The average rating of this method for long-term bankruptcy is over 96%. However, morphological characteristics of the frequent fault labeling are unfixed. usual CNNs are classified by removing morphological features. Errors with fixed morphological characteristics are easily resolved, so that the detection rate is not high.

Surface Inspection and Defects of Hot Rolled Steel Plates :Controlling Three-Dimensional Lightweight Glass Pipes There are three major steps in the steel industry, including durable construction, hot rotation and cold consumption. With each step, the shape of the iron size changes according to its characteristics. This article focuses on the identification of light distances on hot-rolled steel plates. All samples were collected from a number of control systems mounted on a high-speed steel production line developed by Xu et al. [30]. Due to the harsh environment of hot rolled lines, consistency and sample transparency are often poor.

II. LITERATURE SURVEY

A. Review Stage

In this segment various types of fault recognition procedures in various surfaces are reviewed and described briefly as follows.

The titanium coated surfaces may contain small defects, which can be detected by contrast adjusted Otsu's method [1]. Here, the defect can be analysed by thresholding method, converting the grey scale image into binary in the preprocessing. The areas of the image containing similar properties are segmented initially, so that a black and white binary image is obtained. The thresholding converts the image pixels in terms of zero and one, a specific value less than zero is considered as black and pixel values beyond certain standards are assumed as one (white). The above mentioned thresholding method calculate a maximum cut off value for image dissimilarity and then calculate the threshold using Otsu's thresholding. The threshold is calculated by separating the image in to two sections based on the threshold value as the extreme cut off value for image which provides a unimodal histogram. Then the image is transferred to a binary illustration, the otsu's approach espouses that the histogram of the image is bimodal and split the unimodal distribution. This thresholding technique separates the segmented image into two regions, coated regions and uncoated regions. The various kinds of cracks in TFT LCDs (Thin Film Transistor Liquid Crystal Display) can be identified by optical interference pattern sensing technique and neural network classification technique [6]. The optical interference pattern sensing scheme [7] identifies the interfering borders, then further processing can be done by image processing tools. The various types of defect occurred in TFT LCDs can be identified based on the neural network classification method [8].

For producing the interference patterns in TFT LCDs fluorescent lamps or sodium lamps are used. The image is transformed then to grey scale image and also histogram equalization would be completed. The extracted features are then used for classification purposes. The neural network would be classified on the premise of the trained set of images. The grouping is predicated on the width of the fringes, area of the fringes and ratio of the interference fringes obtained. By using neural network classification method the area containing defects and the types of defects occurred can be identified [9]. By using this process the mean square error can be reduced. The defect detection based on interference pattern detecting scheme and neural network classification method is found to be very robust and reliable

Xiaolong Bai proposed a method for detecting defects in automated chips based on template images [10]. Two steps are involved in defect detection process. The primary phase is to gather salient sections of the trial images. The next phase is to relate the variation among the salient sections in the trial images and the consistent areas within the fault free trial images; Phase Only Fourier Transform is intended for saliency detection [11]. The inspections of dies are carried out one by one. For the analysis of salient regions, the captured images are organized in an array and the defect free regions are removed by utilizing the self-similarities among the array of multiple images. Salient regions are easily obtained from the test image array. The defect detection can be done by using template matching [12][13] based on spatial misalignment-tolerant metric [14]. This technique is a simple and easy method for analyzing defects because the normal regions in the image are expeditiously removed in the primary step and further comparison can be done by using template matching in the second step.

Bin Gao introduced a method for analysing defects in metal surfaces based on waveguide imaging with adaptive sparse representation [15][16]. The technique used here is automatic detection so that there is no need for selecting the frequencies manually for defect detection. The core of the strategy could be an intelligent machine learning algorithmic database based on sparse non-negative matrix factorization [17]. For adaptive learning and control sparsity of the factorization, an inner functionality is comprised in the algorithmic program. The algorithm should provide higher accuracy in defect detection process, Bayesian statistics methodology is used for obtaining this high accuracy [18]. The learning process using sparse representation from underlying data statics doesn't use prior information of the fault bands. The defect detection uses waveguide imaging system. For analysis the anomalous patterns in waveguide images, sparse representation is used. The sparse representation method detects the defects automatically in sparse-frequency domain [19]. The mining of the spectrum marks related to the fault is signifi cantly very economical by applying optimal sparsely, which gives higher detection performance in metal surfaces

The defects in mandarin fruits could be detected by using fuzzy image thresholding and defect classification by using linear classifier model [20]. The feature extraction for classification purpose is done by applying Binary Wavelet Transform (BWT) [21]. The block diagram of pattern detection and classification algorithm. Image enhancement and segmentation were used for pattern recognition. An efficient methodology was applied for image thresholding [22], preferably fuzzy set theory. The details about grayness ambiguities present in the image is provided by the measure of fuzziness. A combination of fuzzy image thresholding, BWT feature values and linear classifier model were used for external fault recognition and classification using pattern recognition method [23]. The faulty spaces are isolated by segmentation using fuzzy image thresholding. The combination of fuzzy thresholding and BWT was a binary scaled image. The background of this binary image and non-feature components enclosed in the image are suppressed and it shows only the complete outlook. The feature values are calculated from the diagonal details plotted in scatter plot. The linear classifier model is trained by using pattern recognition model. In this defect detection and classification scheme, target adaptation scheme is applied for training process. The target adaptation scheme was almost equal to perception algorithm to fetch the output of classifier closer to the predefined goal. Here the classifier fails to classify accurately, so the training procedure is reiterated by using the feature values in a two class discriminate scrutiny

There may be some defects on the bearing surface which can be analyzed by gathering CCD images and applying image processing based on machine vision technology [24]. Detecting the bearing position / area using least square mounting and annulus scanning is the main step. In the second step, convert the circular image to a rectangular image and use the filtering and segmentation features to improve the image quality. In processing, image enhancement, low pass filtering, sharpening and morphological processing are used to improve the quality of the acquired image. Contrast stretching and median filtration are also used in the pretreatment. Image segmentation uses the Otsus method. Particle swarm optimization algorithm [25] is used to detect defects on the surface of solar panels [26].

This algorithm as the main part of the proposed methodology, which is preferred to obtain the edges of the image. The different steps in image processing are shown in Figure 3.The cracks and bus bars are analysed using edge detection technique [27]. The classification depends on location of bus bars in the solar cell panel. After edge detection, the image containing cracks and bus bars were analysed and the grouping of pixels based on similar features and different grey values were done. By this manner it could be able to acquire desired information's like cracks, that they have dark grey pixels. The bus bars and cracks were identified by counting the number of dark grey pixels [28].

There were two types of classification used in the system, first one was classification of cracks and second one was normal and defective product classification. The fuzzy logic classification methodology was used for classification of defect in solar cell panel. A PLC (Programmable Logic Controller) was used to separate the defective products, it would reject the product which contains defect. This technique gives good defect detection result

Gagen Kishore Nand presented a method based on entropy segmentation for defect detection of steel surfaces [29]. Here, in the preprocessing step illumination compensation could be done by applying inverse illumination to discard irregularity of light intensity presented in the image. After that the defected regions were detected by using local entropy of the image. He also suggested a dynamic updating concept which was useful to identify the background of the image. This methodology also provides an efficient way to classify the faults based on defective and non-defective regions. The defective regions from the entropy images were extracted by using background subtraction methodology. This entropy image was obtained from the comparison between the entropy of the image and the entropy of background.

To obtain segmented images, a threshold method based on histogram is used [30]. The histogram-based method successfully identified steel surface defects such as water drops, blisters, and scratches. Circular area projection histogram (CRPH) method and sparse representation method are used to analyze the defect on the surface of the bottle cap [31]. In this method, the center of the image is mainly set. The next step is to obtain the appropriate radius circle area as the area of interest (ROI) on the surface of the standard sheath. The ROI is projected as a histogram in completely different directions rotating along the center of the image. Histogram is a series of specific distribution distributed by calculation

These sorts of arrays are deliberated as atoms which generate the template dictionary. Then the trial image is obtained and associated ROI was extracted. The 1D array like sample projected histograms are obtained by projecting the ROI at vertical and horizontal directions. In the fi nal step, the sparse representation method was used to detect the defect by comparing the fragments within the template dictionary to the histogram sample. It is found that sparse representation algorithm is effective for defect detection in bottle caps. Texture analysis is one of the popular methods for surface fault recognition in industries [32].

The liability credit on surface of hot rolled steel sheets using texture feature extraction using a three level 2-D Haar wavelet transform [33] and artificial neural network classifier. In the image analysis process, Haar basis function was used for studying small complicated details in the image. The captured image was treated with Haar wavelet packet decomposition at every scale produces a large set of coefficient matrixes. The next level decomposition coefficients are obtained by using matrix with high energy value. For each coefficient matrix was calculated, which represents the energy.

So that the channel with highest energy value and dominant frequency were used. Therefore this method of defect detection was much more robust and efficient. An ANN classifier with 2-layer feed forward back proportion was used for image classification purpose. It is configured with 15 input nodes corresponding to 15 input features with hidden layers were used. The output node was used for the classification of feature vectors in defective or defect free classes. In the training process, the value of 1 was assigned to samples with defects and 0 is assigned to samples without defects. The response was compared with the desired target and a classification matrix was created, which helps to provide the information about the performance of the classifier, which was expressed in terms of percentage.

This method was suitable for checking surface defects of low resolution and non-uniform lighting images. An automated method used for crack detection system for analyzing cracks in steel slabs [34][35] which occur during casting process of steel production tonnage. The defects are analyzed by using 3D images of steel slab surfaces. It can be done by using morphological image processing and statistical classification method. In the preprocessing step the slab regions were identified, then compensating for slope, handling occluded data and removing of noise are carried out. Segmentation technique was used for extracting the crack length in the steel slab surface and eliminates the pseudo defect areas similar to defect. No cracks were incorrectly perceived in regions where manual review absolutely dominated out the presence of flaws. The accuracy is low because some cracked regions were completely missed.

A high speed segmentation system integrates wavelet transform [36] and Chan and Verse (CV) model was proposed for crack detection in industrial CT images [37][38].The rough edges were detected by applying 3D wavelet transform, and then region growing was used to obtain cracked regions. The edges of cracked body were captured based on resulting volume data and 3D CV model. In this method, wavelet modulus-maxima was used to locate the rough regions. It lessens the volume of C-V model processed data. It also affords primary contour surface which would speed up the convergence of CV model [39].

A hybrid approach consists of CV model and wavelet transform was used for quick segmentation [40]. In the primary step 3Dwavelet transform is used to obtain the irregular sections. Then 3D CV model was used for segmentation of cracked bodies. The implementation process of the technique is shown in the Figure 4. Fuzzy C-mean clustering was applied for detecting defects in potato [41].

The defected areas are detected using Euclidean distance. The various types of defects in potato like rotten, cracks or greening are analysed using this method. The segmentation is based on the image pixel values. Fuzzy C-means clustering and modified fuzzy C-means algorithms are used for detecting defects in potato. The modification in fuzzy C-means algorithm is used to reduce algorithm complexity and make it suitable for real time application. The values of the pixels in the image are compared to check whether or not the pixel belongs to specific cluster [42], it has the values between 0 and 1. The strength of the values of the pixel determines the position in the cluster. The overall pixel values in all clusters is equal to one. If the membership value of a specific cluster is high, the pixel has more possibility to fall into that cluster.

III. PROBLEM STATEMENT

Second, the multi-level probability of the border operator (mpb) is used to detect edges in ROI. The previously obtained prior information is again used to determine the probability of edges that belong to the contour. By creation complete utilize of prior information to improve the edges of the thread contour, the correctness of projected method is improved. Under low contrast conditions, noise and shadows, the contours of internal components are effectively extracted from the component images. In the proposed system classification, feature extraction and classification are followed by CNN layers, and metal hole parameters are classified according to position accuracy, cylindrical character, concentricity and surface roughness. Surface quality is a basic parameter for steel sheets. In the steel industry, manual inspection of a fault is a tedious task. Therefore, it is difficult to ensure the reliability of the defect-free steel surface. To meet user needs, vision-based automated steel surface exploration strategies have proven to be extremely powerful and universal solutions over the past two decades1. The input comes from NEU Surface Defect Database 2, which is available online. The database contains six types of defects, including cracks, inclusions, plaques, coated surfaces, scaling and scratches.

The challenge is to provide an effective and powerful way to use computer vision or machine learning to detect and classify metal failures. Image processing techniques (such as filtering and extracting features from images) are a good solution for training models from which we can determine which type of steel plate is defective. The solution can even be used in real-time applications.

IV. METHODOLOGY

If you CNN can be seen as a particular case of artificial neural network (ANN), motivated idea of effortless or multipart cells in biological visual cortex. The visual cortex contains cells that are sensitive simply to local friendly fields. Compared to the traditional fully connected ANN, the neurons or units of the CNN are arranged in a square draw card, and each neuron on the function card in each layer is only thinly connected to a small number of neurons. CNN is an end-to-end automatic learning model that requires almost no manual design. It builds a workable architecture, combines feature extractors and graders, and works directly on the original pixels in a two-dimensional image. The widespread use of shared weights in CNN can reduce the number of parameters. As we all know, high-level features are class-sensitive, while low-level features are universal. Therefore, advanced feature representation is more useful and critical for classification. CNN distinguishes itself by extracting and forming useful hierarchical feature representations from low to high levels. These distinctive representations can enhance the classification performance. The intricate coat is the core component of CNN. Parameters for a coat entail of a usual of learnable sieves that have a small receiver field but extend to the full complexity of say size. During forward passage, each filter convolves the width and height of the input volume, calculates the dot product between the filter input and the input, and generates a flattened activation chart of the filter. As a result, the network learns a filter that is activated when a particular type of feature is detected at some spatial location in the input. Stacking of activation maps of all filters along the depth dimension to form the complete output of the intricate layer. For the acquired image, a contour extraction method is proposed which can be divided into the following steps. First, use a predefined filter to get a starting point called a priori information about the component and define multiple regions of interest (ROI) based on this.

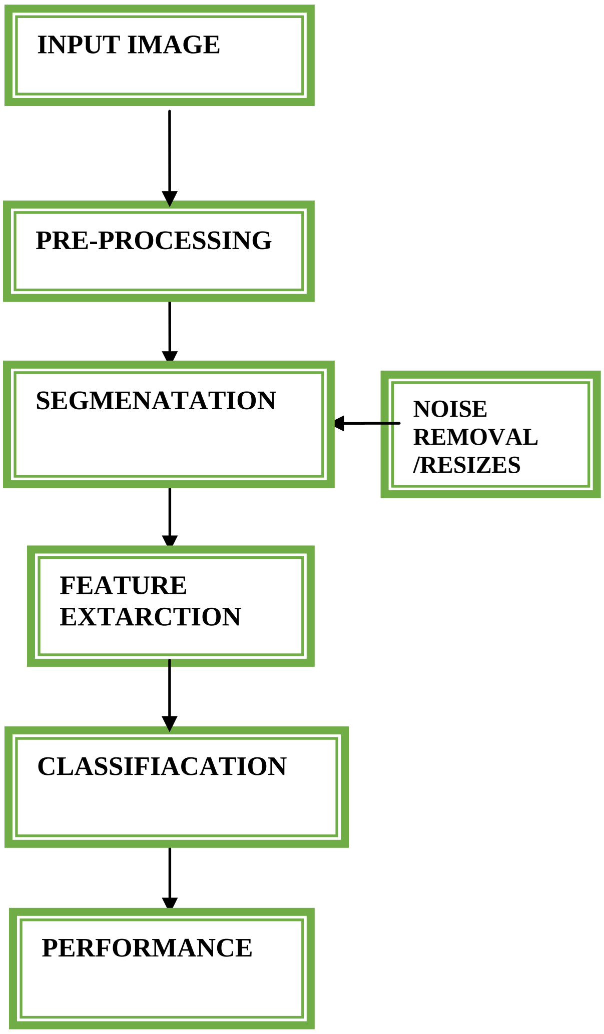


Fig1 proposed flow chart

Pre-processing: Pre-processing refers to "preparation" of samples / images to introduce them into the algorithm for a particular task: target tracking, recognition, feature extraction, etc. Data dispensation is a data removal technique that involves converting raw statistics into a understandable format. Actual data is often partial, inconsistent and / or lacking certain behaviors or trends and may hold many errors.

Image segmentation: Three solutions are expected in the leaves, backgrounds, viruses and green petals. We can assemble a K-mean group by scaling the HSV image. Feature extraction Feature extraction is a basic step in the algorithm for recognizing an object. It refers to the process of information (called operation) from the input image. The features that are taken must be representative and have a great and unique effect on the image. The SurfDetect. m function is the most important entry point for performing feature extraction. This function accepts 8-bit or 8-bit grayscale RGB images for access. The returned product is an interesting piece. This feature includes the following phone calls that include GPU integration calculations:

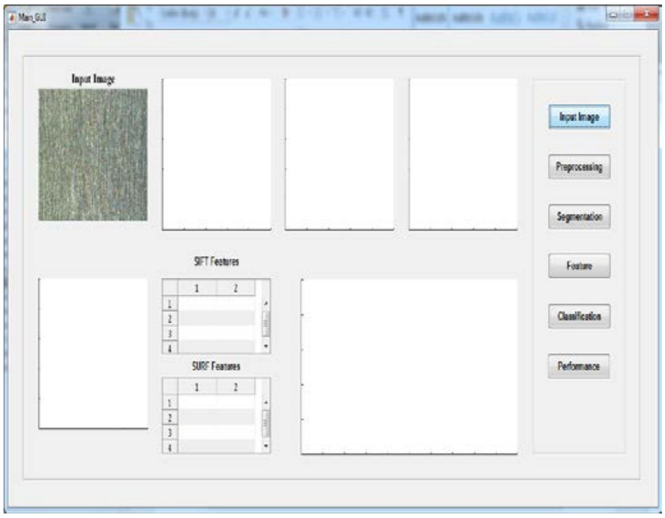


Fig .2 Input images

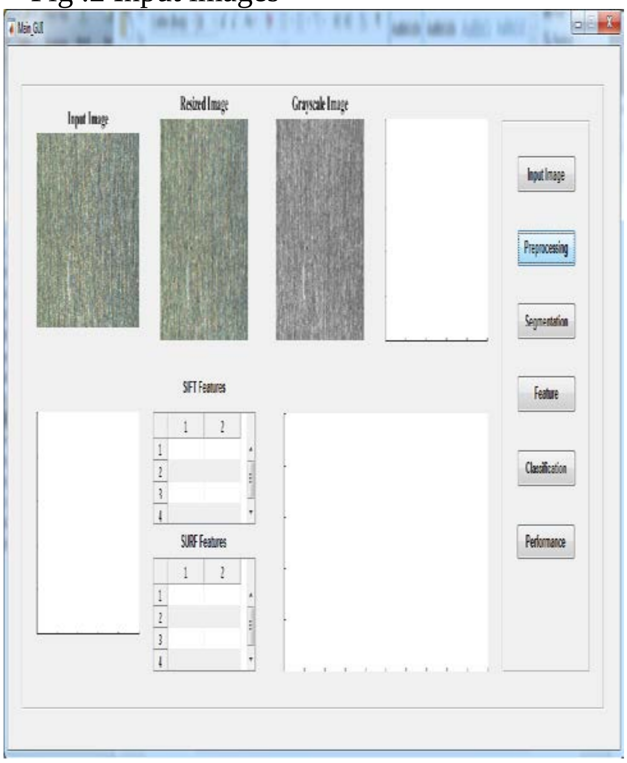


Fig .3 pre-processing GUI window

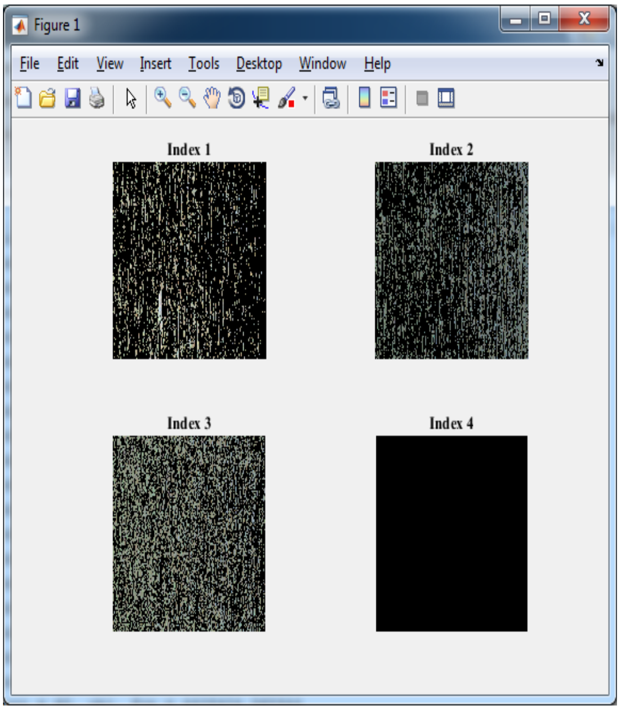


Fig .4 segmentation image

Image Segmentation: Three clusters are expected from the leaf image, background, infected and green clusters. We apply K-means clustering on the Hue component of the HSV image

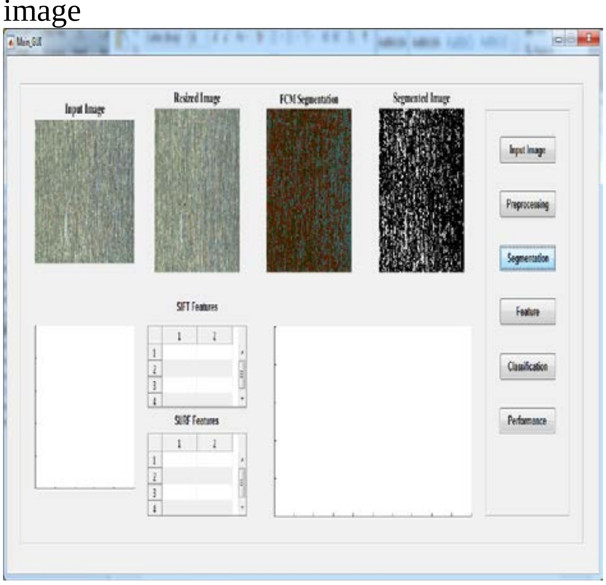


Fig .5 FCM Segmentation GUI window

SURF: SURF is similar to DoG filter. Use a square instead of a simple Gaussian image, because the coincidence with a square is faster when different images are used. Again, it can be made with different scales. SURF uses a BLOB detector based on Hessian maturity to find interesting sites. For the mapping function, we use a response to the spherical and vertical directions with appropriate Gaussian values. For reference, SURF also uses wavelet results. Select the vicinity of the keyboard and assign it to the territory, and then for each region, select and submit the response provided by obtaining SURF definitions. The Laplacian signal used for the test is used in the main plot. The Laplacian icon separates the bright colors from the dark shadows behind them. In the case of matching games, the users only match if the features are in the opposite form (based on the symbol), which makes the game faster.

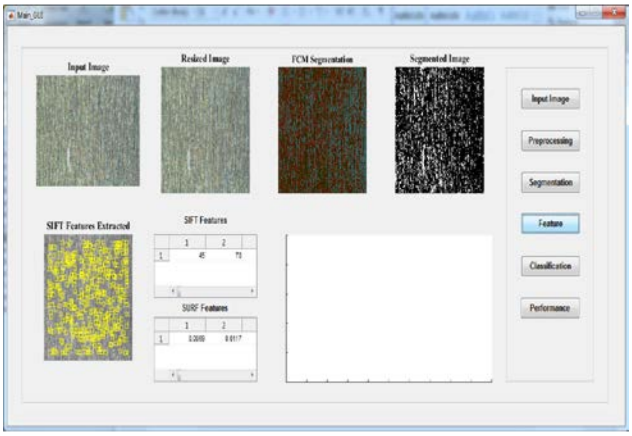
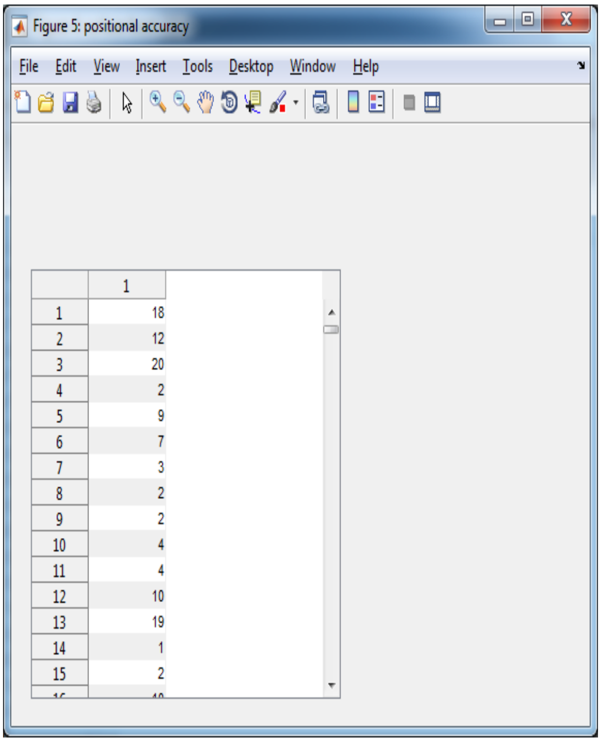


Fig .6 Feature extraction GUI windows

There is a lot to consider when removing these functions and how to handle them. The SIFT feature provides a series of articles that are not subject to many difficulties in other ways (such as scaling and rotation). Although SIFT images allow for larger images to occur, they allow multiple objects to be captured in the same location, which are taken at different locations in the environment.



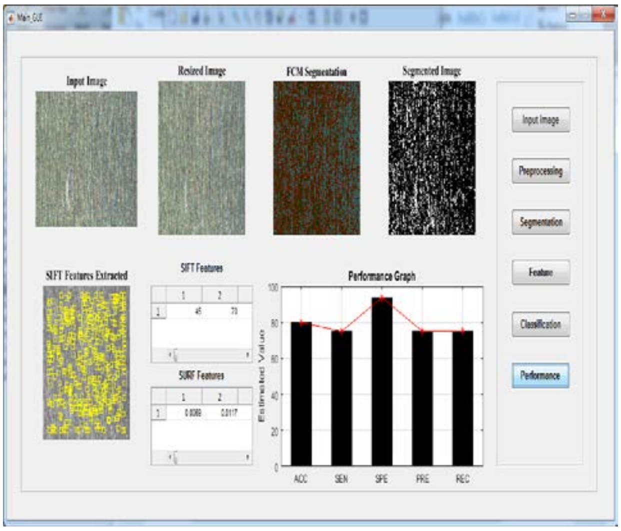


Fig .3 classification GUI windows

SIFT: SIFT provided by Lowe solves unique image rotation, affine transformation, amplification and change of view. The SIFT algorithm has 4 main steps. The first is to use the Gaussian difference (DoG) to calculate the mean values of the scalar fields. Second, location keys are candidates for finding and improving key points by eliminating conflicting points. Third, the orientation distribution of the main points based on the local image, and finally a document generator to determine the local image description of each subject based on the size of the image and path they have [3]

Table 1 Result parameters

Parameters	Dataset 1
Accuracy	80%
Precision	75%
Sensitivity	100%
Specificity	94.11%
Recall	100%

V. CONCLUSION

In this article, we propose a new method for building deep networks, called steel plate defect detection and network design. It combines relevant knowledge of traditional functional processing with the representational ability of deeply entangled networks. Given that the segmentation results are not accurate enough to predict classification, there may be detection of small area errors, we constructed a refined network. A refining pipeline consisting of several typical traditional methods corresponds to a simple network with an empirical threshold. Then, the simple network is converted to an intricate network, and the threshold is released to improve adaptability and achieve end-to-end training. This article now evaluates different surface detection methods based on imaging methods. Using different methods in imaging, digital imaging technology is very useful for analyzing various surface defects. Each method has its advantages and disadvantages. It can be understood from this review that some methods have faster speeds but lack correct accuracy while others have higher accuracy but are limited by complex calculations, resulting in reduced speed. For real-time processing, high speed and high precision are essential. This review shows that each method is suitable for detecting certain defects. Therefore, it can be concluded that a general technique for detecting all different types of surface defects has not been proposed at the same time, so for industrial applications techniques based on different imaging steps will be essential..

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