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Remote Sensing Image Fusion based on Improved Super-Resolution Convolutional Neural Network

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Abstract. Automated Inspection Method (AIM) can be used in various industries, and in today's factory automation production lines. Currently, most production lines will not operate without AIM equipment. In the traditional processing method of AIM requires engineers to spend a lot of time defining characteristics and algorithm development, and very sensitive to sample characteristics. As long as another batch of samples is changed, the characteristics and algorithm parameters must be redefined. Therefore, this study uses artificial intelligence deep learning methods to conduct research on Automated Inspection. Taking copper foil images as the research object, the convolutional neural network (CNN) algorithm is introduced to propose a defect classification method. The main contributions improve the accuracy, stability and flexibility of the AIM inspection method. It was confirmed that this method can successfully perform image pre-processing and defect detection in real time.
Keywords: Automated Inspection; artificial intelligence; manufacturing inspection; convolutional neural network (CNN).

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1. **Introduction.** In recent years, smart vision technology has advanced day by day, hardware prices have dropped, and software tools have become diversified, which has led to an increasing range of applications of AIM in the manufacturing industry.

1.1. **Background.** In the past, the traditional method of AIM inspection was mostly based on engineers lighting the sample. Next, the image is pre-processed and features are defined, and finally defects are detected using the Rule-Based method. With this method, as long as a batch of sample types are changed, the engineer must redefine the features and plan the defect detection rules. When the sample image becomes better, as it becomes more complex, the time it takes engineers will increase a lot. Therefore, traditional methods have gradually begun to transform into artificial intelligence machine learning and deep learning detection methods, using learnable algorithms to allow computers to learn autonomously instead of manually defined features to achieve high accuracy and high stability detection methods [1].

Because the traditional inspection method requires engineers to spend a lot of time defines characteristics, and today's products are characterized by customization, diversity, and high complexity, and it is very time-consuming and difficult to define characteristics. For example: the types of balls produced by golf ball manufacturers are very There are many kinds of balls with different colors, including white, yellow, pink, etc. Each type of ball has flaws in the manufacturing process. It is not easy to define the characteristics manually. Copper foil manufacturers have different surface textures of their products. It is not difficult to detect defects with certain regularity, but it is quite difficult when the detected defects are classified through manually defined features because the defects are too similar to each other. Therefore, the best way to solve the above problems is to use artificial intelligence deep learning method, introduce learnable algorithms, and let the AIM equipment learn features by itself to replace the traditional AIM detection method [2, 3]. The object of this study is copper foil. First of all, in the copper-related industries, It use changes in gray scale values to detect defects in copper strips and use Fuzzy Classification to classify defects [4, 5]; It used sample comparison to detect defects in copper strips [6, 7], and then used machine learning algorithms such as BP Network (Back Propagation Network), RBF (Radial basis function) and SVM (Support Vector Machine) to implement defect classification [**?**]; Wang et al. used image subtraction and image segmentation algorithms to successfully detect defects in copper rods [12]; Li et al. used wavelet transformation, SVM and threshold methods to identify defects in copper foil substrates. Classification [**?**]; Guo et al. used wavelet transformation and sample comparison methods to successfully solve the problem of PCB circuit board defect detection [16]. There is no trace of deep learning in the above copper-related industrial applications.

1.2. **Purpose and contribution.** The purpose of this paper introduces the method of artificial intelligence deep learning into Automated Inspection to improve the accuracy, stability and flexibility of the AIM inspection method. This contribution of this article will use the CNN algorithm as a basis to design a system for the copper foil industry and develop a Deep Learn-based defect detection method. In order to meet the needs of various factory environments, in addition to selecting the camera according to the imaging mode and sensor, the sensor color mode, resolution, pixel size and shutter method can also be selected according to different needs.

2. Relative work.

2.1. **Automated inspection method.** Automated Inspection Method can be seen in various industries, and in today's factory automation production lines, AIM equipment is an indispensable link. This method requires engineers to spend a lot of time defining characteristics and developing algorithms, and traditional methods have limited sample characteristics. It is very sensitive. As long as another batch of samples is changed, the characteristics and algorithm parameters must be redefined. The appearance complexity of today's products is increasing day by day, and small-volume and diverse production has become a trend. The industry has begun to feel the need to use deep learning artificial intelligence to assist in the development of AIM systems. Deep learning methods does not require program developers to define features. It allows the computer to learn image features on its own, as if it is imitating the human brain. The most famous deep learning algorithm in the imaging field is Convolutional Neural Network. Examples of this method in industrial defect detection. Santur et al. [1] used the CNN method to successfully solve the problem of defects on the track surface; Kim et al. [4] used CNN to identify defects in the semiconductor manufacturing process [4, 5]; Sun and Long [6] used CNN to detect fabric defects; Zhong et al. [7] used CNN to detect whether tires have bubble defects. In raiway applications, Zhong et al. [7] used CNN to detect defects in cotter pins of high-speed raiway suspension support device systems [8]. In the application of machining, Khumaidi et al. [8] used CNN to identify welding defects. Applications in agriculture, Azizah et al. [9] used CNN to identify defects in mangoes. In the application of face recognition, Han et al. [11] used CNN for face recognition and implemented gender classification and person counting. Next, some people used the recognition ability of CNN to make a difference in image positioning and target detection. Some people proposed algorithms such as RCNN (Regions with CNN features) and Fast-RCNN. Shi and others used Fast-RCNN to locate fiber paper. defects; Han et al.[11] used Fast-RCNN to detect defects on the surface of the wheel valley; Lee et al. used Fast-RCNN to successfully locate the text on the stone slab. The above CNN-related algorithms are a kind of supervised learning (Supervised Learning) in the field of artificial intelligence, which means that the computer must be told what kind of sample it is (such as: defective and non-defect) before learning, and in order to solve the problem, it must provide sub-like the complicated process of information [**?**].

Yang et al.[14] use the Stacked-Auto encoder algorithm to automatically classify plants, which is the automatic grouping algorithm; Yang et al.[14] use the Convolutional Auto encoder algorithm to detect abnormalities in temperature sensors; Mei et al. [15] used the Convolutional De-noising Auto encoder algorithm to detect defects in LCD panels. They only need to give the computer a sample of one type, and the computer will learn and find samples that are different from this type, which is the so-called One Class Learning [16, 17]. It can be seen that deep learning is indeed the trend of this era. It has greatly solved the difficulties in the AIM field and greatly improved the detection rate and stability of AIM equipment.

2.2. **Neural network.** Neural network is an algorithm with learning ability that imitates the human neural brain. It can imitate human learning through a series of complex mathematical models and occupies a place in the field of artificial intelligence. A standard neural network has a structure of three layers, input layer, hidden layer and output layer, and then uses some mathematical models to continuously correct the weight and bias to achieve the learning effect. Such a network architecture is basically divided into forward pass and reverse pass. The action of forward pass means that given an input data, the convolution layer and the pooling layer are then used to perform internal operations of the network [**?**].

2.2.1. *Weight and bias.* There is a bias neuron in each layer of neurons, with a value of 1. Its purpose is to give the neural network one more dimension, so that the network is not limited to the origin, to improve overall learning and decision-making capabilities. Activation Function: The excitation function is the decision-maker of the entire neural network. After each neuron is weighted by the weight and bias, it must use the excitation function to review whether the neuron is triggered. The Sigmoid function is a function of the degree of attribution. When the input value is larger, the output is closer to 1. On the contrary, the input value is smaller, the closer to 0; Tanh (Hyperbolic Tangent) function, which is very similar to the sigmoid function, is a binary classification function, when the input value is larger, the output is closer to 1, and vice versa, the closer to -1. Sigmoid and Tanh are often used in decision-making and classification situations. The Relu function is a linear function. When the input value is less than 0, the output is 0. When the input value is greater than or equal to 0, the output value has a linear relationship with the input value; the Leaky Relu function is to improve the performance of Relu. When there is no output for negative values, a very small slope is introduced at the negative end. Relu and Leaky Relu often appear in regression analysis and real number prediction. In addition to the above four excitation functions, there is also a special function that cannot be graphically represented. It is an excitation function used to describe probability [?].

2.2.2. *Cost function.* The cost function, also known as the loss function, is used to describe the error between the output of the network and the real output. The training of the network is based on this error to correct the weight and bias of the network. Common cost functions are as Formulas (2-1) and (2-2):

$$\text{Mean Squared Error} = \sum_m (Y - \text{GroundTruth})^2 \tag{1}$$

$$\text{CrossEntropy} = -\sum_m \text{GroundTruth}_i \times \log(Y_i) \tag{2}$$

Among them, Mean Squared Error is commonly used in regression analysis and real number prediction, while Cross Entropy, it is most commonly used in probabilistic models, so it is often used in classification problems.

2.2.3. *Optimizer.* The purpose of the optimizer is to correct the weight and bias of the network through the error value of the cost function, thereby achieving autonomous learning of the network. The most famous optimization algorithm in the field of neural networks is the gradient descent method (Gradient Descent). Its weight update method is as Formulas (2-3) and (2-4):

$$\text{Gradient}_t = \nabla E(W_{\text{old}}) \tag{3}$$

$$W_{\text{new}} = W_{\text{old}} - \alpha \cdot \text{Gradient} \tag{4}$$

Where Gradient_t is the cost function of the network output, $\nabla(W_{\text{old}})$ is the gradient value of the cost function to W_{old}, α is the network learning rate, and its optimization criterion is to move in the negative direction of the gradient. At present, all optimization methods are developed based on the gradient descent method. The following are common gradient descent optimization models:

A. Convergence speed and fast calculation speed. Disadvantages are frequent network updates, high noise, and easy convergence to local minimums.

Batch Gradient Descent: Calculate the gradient of all training samples to update the network. The advantage is that convex functions can converge to the global minimum. Disadvantages are slow convergence speed, slow calculation speed, and large memory requirements.

C. Mini-batch Gradient Descent: Divide the training samples into many batches, calculate the gradients separately for each batch, and then merge the respective gradients using statistical mathematics methods (accumulation, average, etc.), and then update the network. The advantage is that it requires little memory, combines the advantages of the stochastic gradient descent method and the batch gradient descent method, and balances the disadvantages of the stochastic gradient descent method and the batch gradient descent method. It is currently the most commonly used method. The disadvantage is that the training network must have one more parameter.

D. Momentum: The momentum method is an algorithm derived in order to retain the speed of the stochastic gradient descent method and improve the ability to resist noise. The specific implementation method is to add past gradients to the original gradient update algorithm to improve stability. The Formulas (2-5) and (2-6):

$$\text{Gradient}_t = \gamma\gamma\text{Gradient}_{t-1} + \alpha\nabla E(W_{\text{old}}) \tag{5}$$

$$W_{\text{new}} = W_{\text{old}} - \text{Gradient}_t \tag{6}$$

where Gradient_t is the gradient at the current time, Gradient_{t-1} is the gradient at the previous moment, $\gamma\gamma$ is the gradient decay rate at the previous moment, and α is the learning rate. The advantages are fast convergence speed and high noise immunity. The disadvantage is that only a single fixed learning rate α can be used.

Adagrad: The optimization methods all have a common feature, which is to use a single fixed learning rate α. Adagrad is an adaptive learning rate optimization method developed to improve flexibility. The basic steps are to first calculate the gradient, then calculate the square of the cumulative gradient, then use the square of the cumulative gradient to continuously update the learning rate, and finally use the updated learning rate to update the network. The specific Formulas (2-7) and (2-8):

$$\text{AGS}_T = \text{AGS}_{T-1} + (\text{Gradient}_t)^2 \tag{7}$$

$$W_{\text{new}} = W_{\text{old}} - \alpha_t \cdot \text{Gradient}_t \tag{8}$$

Among them, Gradient_t is the gradient at the current moment, Gradient_t^2 is the current square gradient, AGS (Accumulated Gradient Square) is the accumulated gradient square, α_{global} is the global learning rate, α_t is the adaptive learning rate at the current moment, and ϵ is a very small constant for the sake of numerical stability. The advantage is that it can adaptively change the learning rate and improve the flexibility of the training network. The disadvantage is that when the optimal solution is not good in the early stages of training, it will be difficult to find a good solution in the later stages [**?**].

RMSprop: In some cases, when the optimization solution of Adagrad in the early stage is not good, it will be difficult to find a good optimization solution in the later stage as the learning rate becomes smaller and smaller. RMSprop was developed to solve this problem. Optimization method, the Formula is as Formulars (2-9) and (2-10):

$$\text{AGS}_T = \gamma\gamma\text{AGS}_{T-1} + (1-\gamma\gamma)(\text{Gradient}_t)^2 \tag{9}$$

$$W_{\text{new}} = W_{\text{old}} - \alpha_t \cdot \text{Gradient}_t \tag{10}$$

Among them, $\gamma\gamma$ is to suppress the frequency of learning rate decrease, and other parameters are the same as Adagrad. The advantage is that the training network has high flexibility and can adapt the learning rate to solve the Adagrad problem.

Adam: Adam retAIMns the characteristics of RMSprop and introduces the concept of momentum to provide a more stable and reliable optimization method. The Formula (2-11) and (2-12) is as follows:

$$m_t = vm_{t-1} + (1-u)\text{Gradient}_t \tag{11}$$

$$n_t = vn_{t-1} + (1-v)(\text{Gradient}_t)^2 \tag{12}$$

Where m_t is the first-order momentum of the gradient, u is the first-order momentum parameter of the gradient, n_t is the second-order momentum of the gradient, and v is the second-order momentum parameter of the gradient.

2.3. **Convolutional neural network.** Convolutional neural network is a deep learning algorithm evolved from neural network. It can extract important features from a set of data through the mathematical model of convolution, and is used in image recognition. The field has made considerable contributions. A standard convolutional neural network, its architecture is shown in the Figure 1.

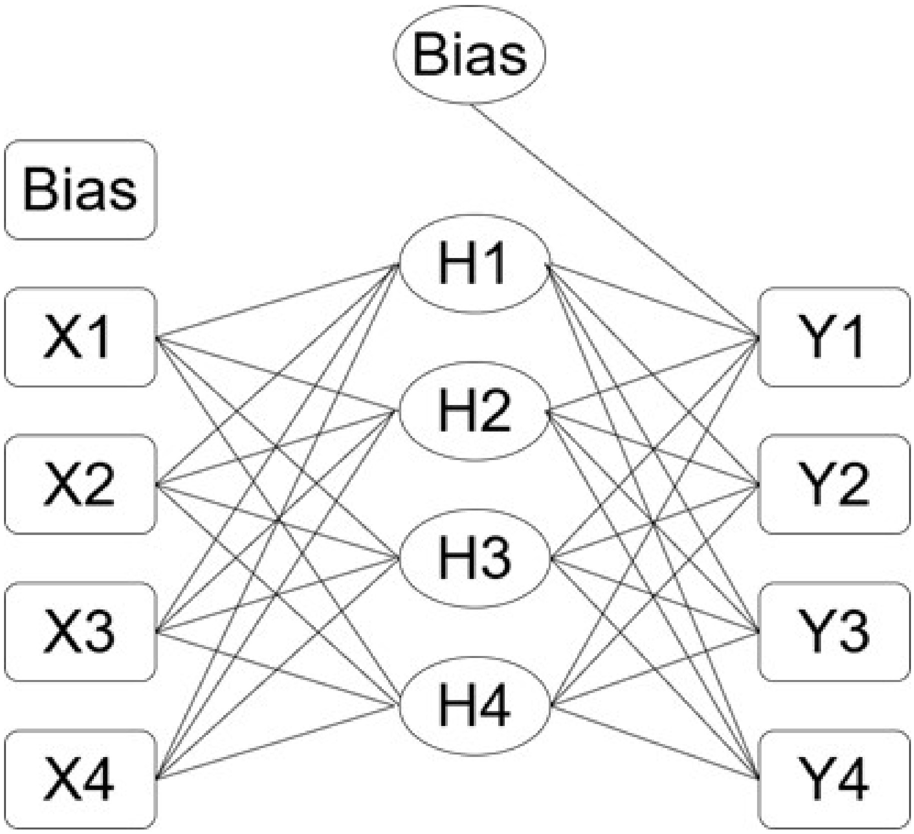

Figure 1. Convolutional neural network architecture diagram

The first half of the network is the core part of the convolutional neural network, using method to extract the features of the input data, and then use the method to perform one-dimensional mapping on the extracted features, and finally then use complete the internal calculation of the network and obtain the Convolutional neural networks also have forward and backward transmission, and their basic structure is completely similar to that of neural networks [29].

2.3.1. *Convolutional layer.* The convolution layer uses convolution to capture high-dimensional feature data. It is the core operation of the convolutional neural network and is often used in image data. Convolution provides a mask, and then scans the input image data. Each scan will perform an operation on the mask and the image. This operation is the same as the weight and bias of the neural network.

2.3.2. *Pooling layer.* Pooling layer, using pooling can effectively reduce the amount of data while retaining the integrity of feature information. Commonly used are the maximum pooling layer (max-pooling) and the average pooling layer (average-pooling).

2.3.3. *Flatten layer.* The purpose of the flat layer is to present the convolved high-dimensional data in a one-dimensional form. In order to match the input format of the fully connected layer.

2.3.4. *Fully connected layer.* Fully connected layer, this part basically refers to the neural network, a whole convolutional neural network. The first half extracts high-dimensional feature data through the convolutional layer, and the second half uses the fully connected layer, converted into low-dimensional features for output [30, 31, 32].he purpose of the flat layer is to present the convolved high-dimensional data in a one-dimensional form. In order to match the input format of the fully connected layer.

3. **Research methods.** The main purpose of this research is to develop an automated copper foil defect detection and classification system for a cooperative manufacturer's copper foil production line. The core of this research is software system design. The software system design is divided into five parts: the first is the camera-side control, which can control camera parameters and image acquisition through the PC-side program; the second is the image analysis algorithm, which includes copper foil defect detection and copper foil defect classification. The purpose of defect detection is to find copper foil defects and locate the defect center. The purpose of defect classification is to use AIM deep learning technology to collect a large number of training samples so that the computer can learn their characteristics and complete AIM-based copper foil defect classification. The third is the manageability of software parameters, which can manage the parameters of all software systems; the fourth is software system monitoring, which can monitor the abnormalities of all software systems; the fifth is communication, which can control the system through TCP network communication. Next, each core module will be introduced one by one.

3.1. **Copper foil software system design.** It will introduce the complete software system. The quality of a software system design will determine the efficiency of automation equipment. The software system is divided into five parts: The first part, CF Linescan, is a line scan camera module. This module is all the control programs related to the line camera, including imaging, Pre-processing, etc., the bottom layer is OpenCV and MIL function library; the second part, CF Image Analysis, is the image analysis module. This module is the core of the entire system and is responsible for processing all tasks of the system and image visual analysis which is divided into two sub-modules, one is the defect detection module (Detector) and the other is the defect classification module (Classifier), CF Parameters Manager, is a parameter management module. This module makes the parameters of the line camera module and image analysis module manageable, using Json data structure as the implementation method of parameter definition; the fourth part, CF System Monitor, It is a system monitoring module. The main purpose of this module is to monitor the status of each system and capture abnormal information and error status in a timely manner. The fifth part, CF Link, is a communication module. This module is responsible for communicating. The terminal communicates and allows the user to control the copper foil system.

3.2. **Introduction to copper foil defects.** Copper foil may cause different defects during the manufacturing process. These defects can be roughly divided into pinpoints, bright spots and white spots. Figure 2, show each defect. Illustration of type defects.

3.3. **Copper foil defect detection.**

3.3.1. *Detection method.* It will introduce the detection method of copper foil surface defects. Since the actual production line of copper foil is transported over a large area by rollers, in consideration of hardware cost and accuracy requirements, the imported AIM optical inspection equipment must be based on one PC and two line cameras. Next, in order to provide the input defect image of the AIM deep learning copper foil defect

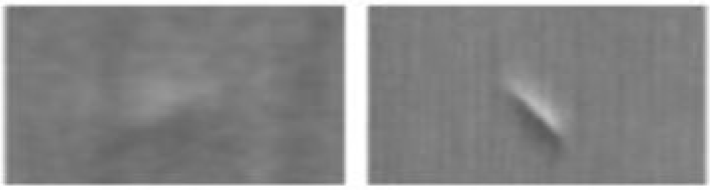

Figure 2. Different pin point defects

classification system, this inspection system must be able to quickly, accurately and stably locate the center of the defect. Therefore, the image algorithm cannot be too complex and the speed requirements are very strict . Figure 3 shows the copper foil defect detection flow chart. The following will introduce each core module of the image algorithm one by one.

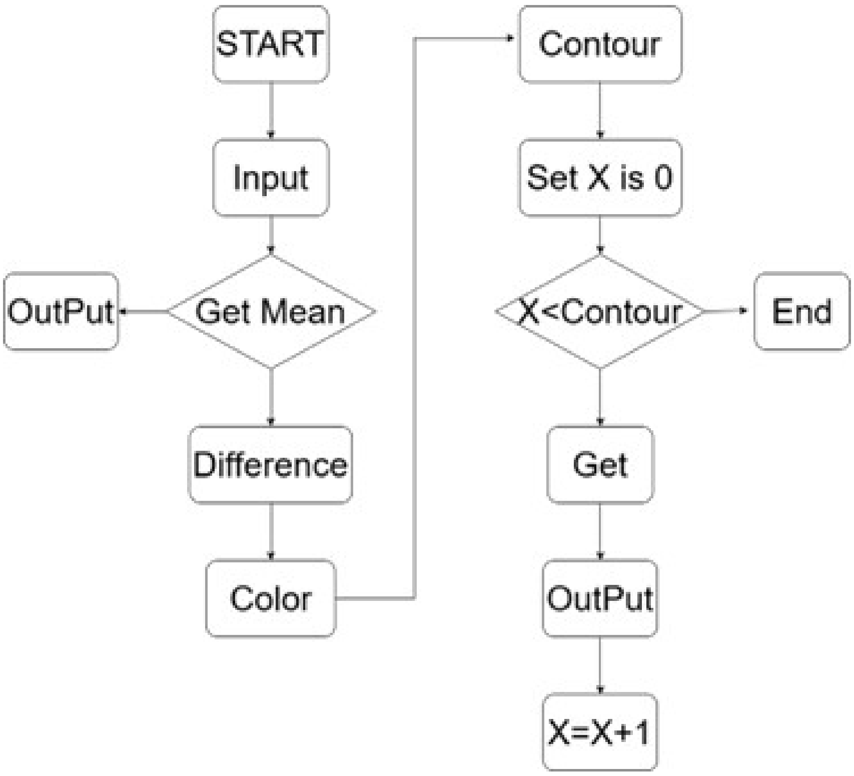

Figure 3. Image detection flow chart

Copper foil itself has similar texture characteristics, so we can use the average value and standard deviation for pre-processing. If it is a copper foil image, its average value will fall within a certain range and its standard deviation will be relatively small. Use this characteristic, we can design an algorithm to filter out non-copper foil images. In addition, the average value can also monitor the copper foil manufacturing process and alert producers of copper foil discoloration. In terms of practical applications, the mathematical operation of the average is weighted average, which is very fast, while the standard deviation has a very fast operation speed because it contains square and root operations. It is not suitable for practical applications, so this system uses the absolute average difference to implement algorithm.

3.3.2. *Reference comparison method.* The texture similarity characteristics of copper foil. Therefore, we use space for time. Before the system goes online, prepare a flawless sample of the copper foil image in the processor memory. We call it a standard image. Through the comparison of the standard image and the image to be tested, anything that is different from the standard image is regarded as a flaw. The specific method of achieving this is through image subtraction. The subtracted image is called a residual image.

3.3.3. *Color threshold.* After the reference comparison method, we obtained a residual image, but at this time we cannot obtain the center point position of the defect, so we must obtain a single-channel binarization through binarization processing. With the binary image, we can use the method to describe its shape, obtain the location of the defect center point, and successfully detect defects. This system uses an RGB color line camera as the imaging device to improve the accuracy of defect classification through color characteristics. The binarization algorithm itself is an algorithm for processing single-channel images. Therefore, we must adopt a multi-channel oriented binarization algorithm, and then convert the multi-channel image into Change to single-channel binary image. In traditional image analysis, the color model conversion method is often used, converting RGB into HSV color model, then taking out the V illumination channel, and performing a single-channel binarization algorithm on the intensity of the illumination. However, due to the fast movement of the on-site production line and the large amount of copper foil image data, in practical applications, we perform a single-channel binary algorithm on each RGB channel and output the RGB binary image. Then we target R, G, and B the three-channel image is subjected to maximum value processing as Formula (3-4), and a single-channel binary image is output.

$$\text{RGB maximum value processing} = \max(IR, IG, IB) \tag{13}$$

I: RGB image, R, G, B: color channel, R, jj: pixel position

3.3.4. *Profile.* After the binarization process, a single-channel binarized image is obtained. Through contour analysis, the black and white areas in the binary image can be divided into multiple objects. Each object is composed of a series of regional contour coordinate points as a data structure. With the coordinate points of the contour, it can be quickly Calculate the center of the area, which is the center of the defect, and finally use this center point as the center of the rectangle to extract a ROI sub-image of a certain size (the width of the sub-image is 176 and the height is 176), and pass it to the AIM deep learning network for defects The classification module performs classification tasks and completes defect detection.

3.4. **Classification of copper foil defects.** It will introduce the classification and research methods of copper foil surface defects. In order to improve the accuracy, stability and flexibility of the classification of the inspection system, this paper introduces the algorithm of deep learning convolutional neural network, which is divided into two stages: training and testing. Through the training stage, the copper foil defect images are processed Features are learned and converted into network models, and the testing phase will use the trAIMned network model for system deployment.

3.4.1. *Copper foil defect classification system architecture.* The method proposed in this paper for classifying copper foil image defects. The complete system architecture is divided into two parts. The first part is the training stage. This stage uses iterative This method continuously corrects the network model parameters to minimize the numerical difference between the labeled category of the input image and the category probability of the output image, and saves the optimized model as a binary file; the second part is the testing phase, using the best results from the first phase. The optimization network model converts the test image into a series of category probabilities through the model, and then finds the maximum probability value which is the corresponding best-matching defect category; Figure 4 is the test stage flow chart.

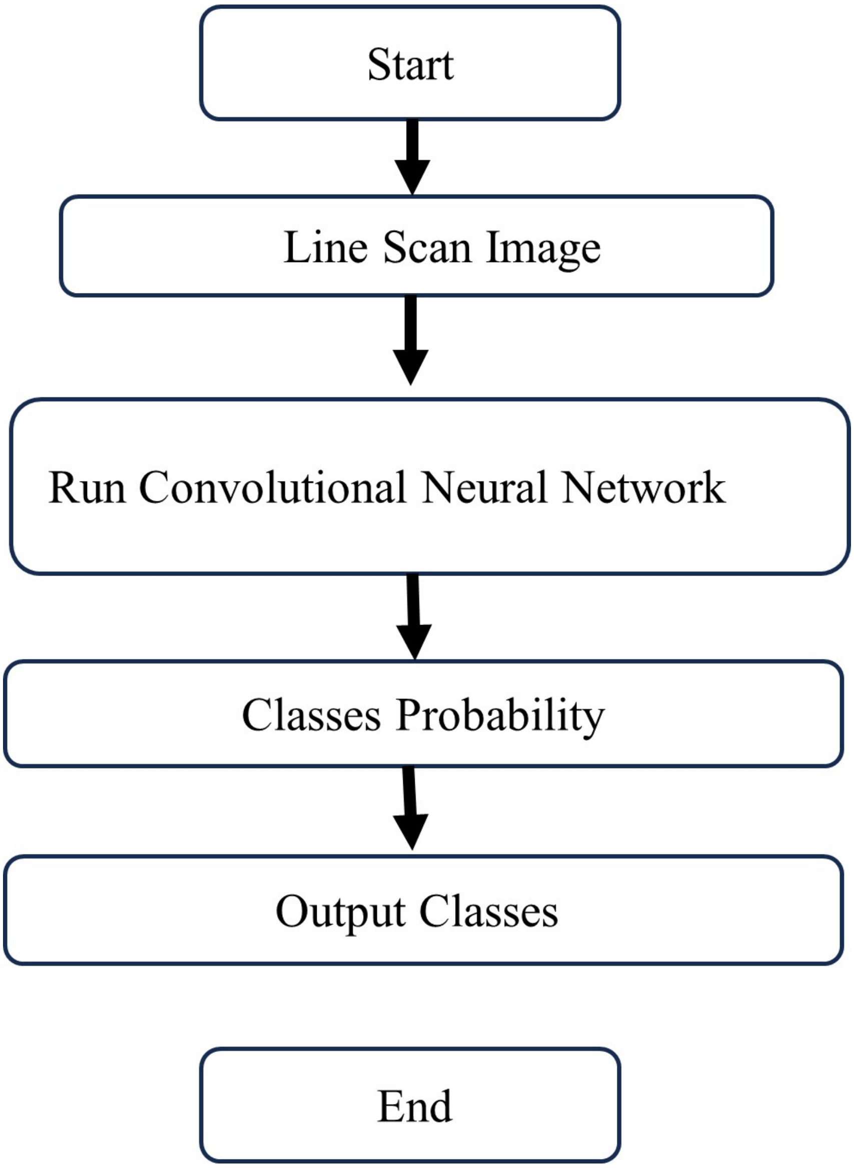

Figure 4. Convolutional neural network testing flow chart

3.4.2. *Deep learning-learning stage.* For convolutional neural networks, positive and negative samples must be prepared during the training phase, meaning good products and defective products. Each set of samples must also prepare the corresponding category, represented by a multi-dimensional vector. The image sample source used in this study is achieved by using an imaging mechanism. When the roller in the production line drives the copper foil to move, the optical rotary encoder in the imaging mechanism will move and rotate accordingly, and then send out a signal to trigger Image capture card, then, the image capture card will trigger the line scan camera synchronously to capture the image. Each copper foil image will go through the copper foil defect detection module to detect the center point of the image sample and capture a rectangular sub-image and store it in the database. After the training samples are collected, since the convolutional neural network algorithm of AIM deep learning we use is supervised learning, the training samples must be manually classified first, and different numbers are given to different categories. When the manual classification is completed, the training stage can be officially entered. The convolutional neural network proposed in this paper is based on the architecture of the classic CNN model Alexnet. Its core architecture uses five layers of convolutional layers. Three layers of maximum pooling layer, two layers of fully connected layer and one layer of Softmax layer realize image dimensionality reduction conversion. Among them, our model is based on the network layer of the Alexnet model architecture, but the standard output of the Alexnet model is 1000 categories, which is too much for copper foil defects. Therefore, we reduce the feature map depth of each layer of convolution in order to improve the computing speed. At the same time, in order to make the network have good generalization, an additional verification data set will be prepared to improve the generalization ability.

Complete training process: First, load the cropped image samples, then divide them into training samples and verification samples at a ratio of 9:1, and then start the iterative training mAIMn program. Each iteration will divide the training samples into N batches (The N value depends on the total number of training samples. We will pack 10 training data into 1 batch), and then randomly disrupt their order. Each batch of samples is input to the core algorithm of the convolutional neural network. There will be two outputs, namely Classes Probability and training Loss. The network will update the weight parameters through the loss value in the form of optimization to complete the process.

One batch training when N batches of training are completed, one iteration is completed, and then network model verification is performed, and the verification samples are input to the convolutional neural network. The core algorithm of the road takes out the validation loss value. After Epoch iterations (10,000 times), the model with the smallest validation loss value will be stored to complete the training of the convolutional neural network.

4. Results.

4.1. System development environment. The system specifications and research environment for copper foil defect detection and classification are shown in the Table 1 and Table 2. A personal computer is used as the processing platform, Visual Studio is used as the software compiler, C/C++ is used as the programming language, and functions are used for AIM deep learning model training. Library BVLC-Caffe, AIM deep learning model inference uses Intel-OpenVINO R4 engine, image processing function library uses OpenCV, line scan camera control uses MIL Library provided by Matrox image capture card manufacturer:

4.2. Experimental results-line camera module - CF line scan. The preliminary inspection mechanism of the copper foil defect detection and classification system. Since the on-site machine of the copper foil production line is continuously running, we must set up the mechanism without affecting the operation of the on-site production line. The mechanism is composed of 30-type aluminum extrusion (side length 30mm) with a single-axis connector, and is set up in a field environment. The connection interface between the mechanism and the optical equipment is connected with a connection plate designed by a 3D printer. .

Uniaxial connectors are designed to allow aluminum extrusions to be connected to each other at specific angles. A 3D printer can use 3D drawing software to create 3D drawings using PLA (Polylactic Acid) material by stacking them layer by layer. It is a set of Quite a convenient device. With the imaging mechanism in the picture above, we can

Table 1. Hardware specifications of copper foil defect detection and classification system

Name	Specification	
1		
CPU	Xeon-E6-2652	
Memory	DDR4 64 GB	
Operating system	Windows	
2		
Model	e2v ELIIXA+ 8k/4k CL	
Resolution	2x8196 pixel	
3	Model	Radient eV-CL
4	Brand	Nikons
Focal length	33 mm	

Table 2. Copper foil defect detection and classification system software specifications

Specification	Name
camera control	MILs
Image processing	OpenCV
AIM model training	BVLC-Caffe
AIM model inference	Intel-OpenVINO

achieve stable imaging without affecting the on-site production environment. Line scan cameras, as the name suggests, have a line of photosensitive elements, which is different from general area cameras. Because the photosensitive elements are of a line, they are particularly sensitive to external light sources. When the line scan camera sensor is not parallel to the line light source, severe vignetting will occur. In order to solve the above problems, a three-axis adjustment base for the line scan camera must be provided to achieve yaw-pitch-roll three-axis rotation, At present, the on-site imaging mechanism can achieve three-axis rotation through a single-axis connector.

After the three-axis rotation of the imaging mechanism and yaw-pitch-roll is completed, a complete line scan image can be obtained. However, since the photosensitive element of the line scan camera is a line, the overall light-receiving area is small. In order to prevent the overall grayscale value of the scanned image from being too low, there are three methods to improve the overall photosensitivity. One is to increase the brightness of the light source, the other is to lengthen the exposure time, and the third is to increase the aperture. Method 1: Increasing the brightness of the light source involves the risk of overheating. To increase the brightness of the light source, it is necessary to increase the current value flowing through the LED chip. As the current value increases, according to electrical theory, power is equal to the product of voltage and current, and the overall power will increase. Therefore, more heat energy is generated; Method 2 lengthens the exposure time. The longer the exposure of the photosensitive element, the brighter the overall brightness. However, since the on-site production line drives the copper foil to move at a certAIMn speed, in order to prevent the scanned image from blurring, the exposure time must not be too long. Long; Method 3: Increase the aperture. The larger the aperture, the greater the light will enter, but the relative depth of field will become shallower and the noise will increase. Therefore, appropriate selection of the aperture size must also be considered. The above three methods are often used to adjust the grayscale value brightness of area cameras. However, for line scan cameras, insufficient light sensitivity may still occur in some situations. Due to the low brightness of the on-site line light source, the high resolution of the camera, and the high pixel accuracy of this system, insufficient light sensitivity may occur. To solve this problem, we use TDI (Time delay and integration) mode to achieve high-exposure imaging. Among them, the principle of TDI is that there is a surface-type photosensitive structure inside the camera. Such a structure can achieve the ability of multiple delayed exposures. When the object moves, the first line of the camera is exposed to light (that is, the first level of the surface-type photosensitive structure), it will not output the image immediately. It will push the first level to the second level to allow the charge of the photosensitive element to accumulate. According to this principle, when it is pushed to the last level, the charge of the photosensitive element will be accumulated and a line will be output. Image, complete the effect of multiple exposures.

After the imaging problem is solved, the next step is the camera control part. The line scan camera we use is e2V ELIIXA+ 8k/4k CL Cmos Multi-Line Color Camera, and the image capture card we use is Matrox-Radient ev-CL. All camera control must be done via the image capture card. The internal parameter setting of the camera can be completed through RS232 serial communication. The basic baud rate is 9600, 8 bits, no parity correction bit, and 1 stop bit. The complete camera parameter setting structure and the serial communication command format. Finally, the camera capture control part must rely on the MIL (Matrox Image Library) function library to control the Matrox-Radient ev-CL image capture card to complete the capture control. At present, we have been able to use the C++ programming language as the basis to call the MIL function library to control the camera imaging.

4.3. **Experimental results- CF parameters manager.** The results specially design a set of parameter management modules for the copper foil defect detection and classification system, in order to efficiently control the parameters of each sub-module on the system. The specific implementation is through the Json lightweight data exchange language. The biggest advantage of Json is that it is easy for people to read, and it is lightweight and does not occupy a large amount of memory. Json is often used as the extension. Currently, this system has imported Json as the data grid for parameter management.

4.4. **Experimental results- CF system monitor.** The results specially designed a system monitoring module for the copper foil defect detection and classification system. The purpose is to monitor the hardware of this system, such as: CPU temperature, memory, temporary register capacity, camera status, abnormal errors, etc.

4.5. **Experimental results-communication module CF LINK.** The results specially designed a set of communication modules for the copper foil defect detection and classification system. The purpose is that in the future this system will be a working machine. This working machine will not be directly operated by production line operators. All the control and data of this system. The capture will be completed by the remote terminal computer through TCP-based ethernet. The specific implementation method is to use CF LINK proposed in this paper to define the communication command format. The bottom layer of this CF LINK is implemented with TCP. It converts all the required control codes of the system into packet commands to achieve network communication control, as shown in Table 3.

Table 3. CF LINK packet format

Start	R/W	ID	Data	Stop
0×01	0×52	0×0e	0×40	0×7e
0×01	0×57	Client Format	0×40	0×7e
0×01	0×52	Client Format	0×40	0×7e
0×01	0×57	0×0e	0×40	0×7e
0×01	0×52	0×0e	0×40	0×7e

4.6. **Experiment results of CF image and analysis.** The results conducts multiple tests on copper foil defect detection experiments. The core algorithm is developed based on the programming language C++ and the OpenCV open source function library. The mAIMn algorithm architecture is divided into two levels. The mAIMn purpose of the front stage is to consider the situation where there is no copper foil on the production line and the system is subject to external interference. The main method can efficiently and quickly determine whether the camera source image is copper foil through the image average and the absolute average difference. The main purpose of the post-stage is to detect defects and accurately locate their centers. Point coordinates, and then store the sub-image of the rectangle outside the defect in the memory, allowing the AIM copper foil defect classification system to analyze and classify it. The core algorithm of AIM copper foil defect classification is to use the Caffe function library to construct a deep learning convolutional neural network and implement AIM training, and then complete the AIM classification through the OpenVINO C++ engine. The biggest bottleneck of this copper foil defect detection and classification system is performance. The moving speed of the copper foil in the on-site production line is about 22 meters per minute, which means it moves 366.67 mm per second. According to the customer's optical specifications, the average one piece is 8192. The acquisition time of 1024*3 color images is about 34 milliseconds. A PC is connected to two cameras, so each within 34 mm, the PC processor must perform defect detection and AIM classification on two 8192*1024*3 color images, which is a very difficult task. Therefore, this paper proposes a solution based on parallel processing and the OpenVINO AIM inference engine. Since the on-site imaging mechanism has not yet been completed, in order to verify the performance of the algorithm, we used software to generate 8192*1024*3 color image samples. Complete test results are in the Table 4:

Table 4. Copper foil image analysis performance experiment

Processor	Image pre-processing	Image defect detection	AIM Classification
I7-8600K	17.6 ms	51.4 ms	5.3 ms
I7-7500	21.6 ms	62.0 ms	6.3 ms
I7-6600	22.5 ms	71.1 ms	7.5 ms
I7-4500	21.5 ms	81.4 ms	9.0 ms

Table 4, we can find that the most time-consuming part of the entire system is the defect detection module, so here we introduce the concept of processing, as shown in the Figure 5.

Figure 5 is divided into three parts, namely line camera, defect detection and defect classification. Among them, one processor PC is connected to two line cameras, and one execution thread processes one line camera. Therefore, there are two execution threads. The complete action process of the line camera execution thread is: first, use the hardware

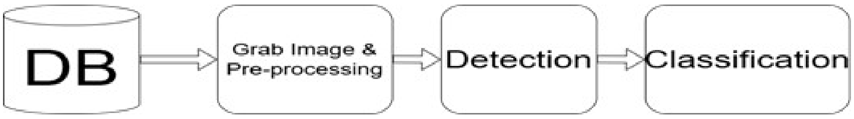

Figure 5. Schematic diagram of l processing

sensor to obtain image, then, image pre-processing. The purpose of pre-processing is to determine whether it is an image of copper foil. Finally, the copper foil image is passed to the defect detection module; the defect detection module is responsible for receiving the copper foil image and completing defect detection. Since this module has a large amount of calculations. Therefore, the module has a total of 6 execution threads, and the flaw detection execution thread has complete actions.

4.7. **Performance analysis.** The process first capture the copper foil image passed by the camera module, then detect defects using the method and finally, pass the sub-images around the found defect center point to the defect classification module. The AIM defect classification module only allocates one execution thread for three reasons. One is because the OpenVINO computing engine greatly improves the speed of AIM inference. The other is generally speaking, the yield rate of copper foil is very high and the probability of defects is not the same. It is not necessary to classify every image taken. Thirdly, because defect classification processes sub-images, it is not like defect detection which needs to process such a large image sample of 8192*1024. The complete action flow of the defect classification execution thread is: : First, capture the defect sub-image passed by the defect detection module, then classify the defects and finally, pass the found classification results to the communication module to complete the classification action. Real-time image pre-processing and defect detection of copper foil images. The copper foil defect detection and classification system captured the copper foil image from the on-site production line. Using the method, it was confirmed that this method can successfully perform image pre-processing and defect detection in real time.

5. **Conclusion and future work.** The results has successfully completed the copper foil inspection system and has preliminary results, which include complete camera control, defect detection and defect classification algorithm design, software performance testing, network communication and parameter manageability, etc. However, due to the system has only been initially completed, and the image samples provided by the cooperative copper foil manufacturers are insufficient. For the image analysis module, a large amount of testing is still needed. In the future, this copper foil inspection system will ask institutional manufacturers to deploy a complete imaging mechanism on the on-site production line and collect a large number of image samples. Then, the software system and method designed will be complete an automated copper foil defect detection and classification system.

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