Qualification Testing of Rebar Electric Arc Pressure Welding Joints Based on CNN-SVM for Apparent Features

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Abstract. This paper presents a convolutional neural network (CNN) and support vector machine (SVM) based analysis model for apparent features of electric arc pressure welding joints, aiming to enhance detection accuracy and replace traditional manual visual inspection methods. The model utilizes a training set of images of rebar welding joints processed by CNN to extract apparent feature vectors through denoising, matrix transformation, convolutional operations, and pooling steps. Simultaneously, the rebar undergoes tensile strength experiments, categorized as qualified and unqualified products. The extracted feature vectors are inputted into the SVM model, establishing a binary classification function model with the tensile strength results, and training the parameters of the CNN-SVM model. Finally, the welding joint test set is inputted into this model for inspection to observe the detection performance. The study demonstrates that the model achieves an accuracy of over 0.95, significantly higher than manual inspection, showing notable advantages.

Keywords: CNN-SVM; Electric arc pressure welding; Tensile strength

1 INTRODUCTION

As the number of high-rise buildings, bridges, and other large structures continues to increase, the demand for the strength and seismic resistance of rebars is also growing. Electric arc pressure welding, as an efficient and reliable rebar connection technology, has been widely applied in construction and structural engineering [1]. However, the quality issues of electric arc pressure welding joints have always been a significant challenge in engineering practice. Traditional welding quality inspection methods typically rely on a combination of destructive tensile strength tests of rebar welding joints and manual visual inspection of welding joints. The rebars subjected to destructive tests cannot be used in the main structure of buildings, where the quality of rebars directly affects the structural load-bearing capacity. Currently, the inspection of electric arc pressure welding joints in the main structure of buildings primarily relies on manual visual inspection, which is subjective, inefficient, and susceptible to environmental

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factors and operator skill levels. This method fails to accurately reflect the quality of welding joints, leading to potential weak points in structural load-bearing capacity. At present, research on the visual inspection of electric arc pressure welding joints for rebars is still lacking domestically. Therefore, seeking a new method to rapidly and accurately assess the quality of electric arc pressure welding joints is crucial for improving the safety and reliability of structures.

With the development of computer vision and machine learning technologies, automated inspection of welding joints has become feasible. Convolutional Neural Networks (CNN), as powerful deep learning models, excel in feature extraction and have achieved numerous successful applications in image recognition and classification [2-3]. When combined with machine learning algorithms such as Support Vector Machines (SVM), more flexible and efficient models can be constructed to address complex classification and regression problems [4-6]. Utilizing CNN-SVM models with samples of electric arc pressure welding joint images from construction sites, real data on the apparent features of rebar welding joints are extracted using CNN. The robust classification capabilities of SVM then categorize the electric arc pressure welding joints into qualified and unqualified products, effectively overcoming the subjectivity, inefficiency, and susceptibility to environmental and operator skill level influences associated with manual visual inspection. Therefore, integrating CNN and SVM to establish an apparent feature analysis model for evaluating the quality of electric arc pressure welding joints for rebars holds significant theoretical and practical significance.

The objective of this study is to construct a CNN-SVM model and train it using a large number of samples of electric arc pressure welding joints for rebars. Through multiple iterations, the optimal number of iterations will be determined, and the parameters of the CNN-SVM model will be optimized. This process aims to provide a more advanced and accurate tool for the visual inspection of electric arc pressure welding joints for rebars, replacing outdated manual visual inspection methods. Additionally, it will offer insights and methods for the visual inspection of welding joints in other rebar welding techniques.

2 THEORETICAL FOUNDATION

2.1 Theoretical Basis of CNN Model

Convolution is a crucial operation in mathematical analysis, primarily used in image processing where two-dimensional convolution is predominantly employed, extending from one-dimensional convolution[7]. Given an image $X \in R^{M\times N}$ and a filter $W \in R^{U\times V}$, typically with U≪M and V≪N, the convolution operation is defined as follows:

$$y_{ij} = \sum_{u=1}^{U}\sum_{v=1}^{V} w_{uv} x i - u + 1,\ j - v + 1$$

The two-dimensional convolution of an input signal X and a filter W is defined as:

$$Y = W * X$$

By performing convolution calculations on the matrices that make up an image, image recognition can be achieved, key feature vectors can be extracted from the image, and the dimensionality of the image matrix can be significantly reduced, reducing the workload for subsequent computations.

2.2 Theoretical Basis of SVM Model

The SVM model is primarily divided into linear and nonlinear models, with a nonlinear model being utilized here. In the classification problem of nonlinear SVM, the SVM model transforms the inner product$(x_i \cdot x_j)$in the transformed space by introducing a kernel function $\mathrm{K}(x_i \cdot x_j)$ into a function in the original space $\mathrm{K}(x_i \cdot x_j) = (\emptyset(x_i) \cdot \emptyset(x_i))$, mapping the samples x to a high-dimensional space H, and performing linear separation of the original problem. After replacing the inner product with the kernel function, the original quadratic programming problem remains convex, ensuring the existence of a global optimal solution. The following dual optimization problem is constructed:

$$maxQ(a) = \sum_{i=1}^{n} a_i - \frac{1}{2}\sum_{i,j=1}^{n} a_i a_j\, y_i y_j K(x_i, x_j)$$

$$s.t. \sum_{i,j=1}^{n} a_i\, y_i = 0$$

$$0 \le a_i \le C, i = 1,2 \cdots, n$$

The corresponding optimal decision function at this point is:

$$f(x) = sgn[\sum_{i=1}^{n} y_i a_i^* K(x, x_i) + b^*]$$

This theory serves as the mathematical foundation of SVM, determining the optimal solution of equations to obtain coefficients such as SVM function weights. This lays the groundwork for classifying multidimensional vector data inputs.

3 METHODS AND EXPERIMENTAL DESIGN

3.1 Basic Approach

The aim of this study is to build an efficient and accurate apparent feature analysis model for electric arc pressure welding joints based on CNN-SVM, replacing traditional manual visual inspection methods.

Firstly, we preprocess the images of rebar welding joints using CNN. During the training process of the CNN model, we apply a series of steps to the images, including denoising, matrix transformation, convolutional operations, and pooling, to extract the apparent feature vectors of the rebar. Simultaneously, we conduct tensile strength experiments on the rebar and categorize the samples into qualified and unqualified products based on the experimental results. These tensile strength data serve as labels for our model, used in supervised learning and model training.

Next, we input the extracted apparent feature vectors from the CNN model into the support vector machine (SVM) model. The feature vectors extracted are compared with the tensile strength experimental results of the electric arc pressure welding joints to establish a binary classification function model for the CNN-SVM model, with outputs of qualified and unqualified products.

Finally, we train the parameters of the constructed CNN-SVM model and input the test set of electric arc pressure welding joints into the model for verification, observing the detection performance. By comparing the detection results with the actual tensile strength data, we evaluate the accuracy and reliability of the model. The algorithm flow is illustrated in Figure 1.

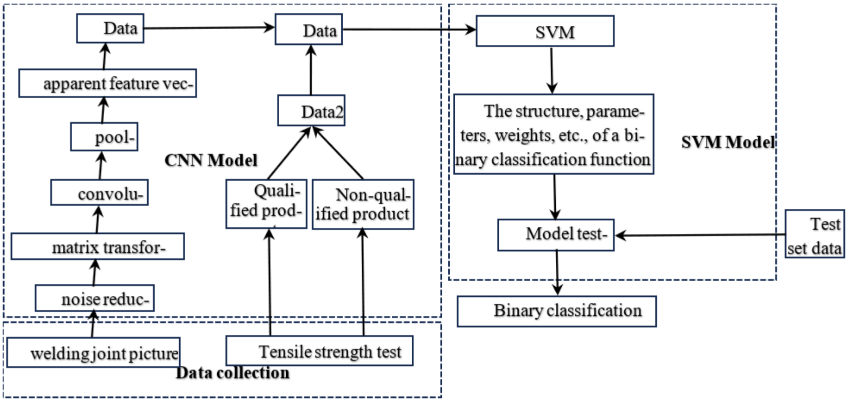

Fig. 1. CNN-SVM Model Algorithm Flowchart

3.2 Data Acquisition

The data consists of two parts: electric arc pressure welding joint images obtained through IoT or manual photography (Data1) and the required strength data for the welding joints (Data 2).

(1) Acquisition of Data1 and the test set

Due to the various limitations and complexities of the testing environment at construction sites, it is challenging to collect data directly for building high-precision prediction models, thus limiting the on-site data collection for electric arc pressure welding joint strength detection. Therefore, the collection of images in this part mainly occurs in the laboratory. We take photos of a large number of electric arc pressure welding joints, collect, encode, and store them to form the training data (Data1) and test set data for our model. Some welding joints are shown in Figure 2.

Fig. 2. Picture of the steel bar electric slag pressure welding joint

(2) Acquisition of Data2

The required strength data for welding joints (Data2) varies depending on different materials and application scenarios. For instance, the tensile strength of ordinary carbon steel welding joints should comply with the standard requirements of GB/T 3323-200, while the standard tensile strength of high-strength rebar welding joints should not be less than 85% of the tensile strength of a single rebar. Welding joints of ordinary steel should generally have a tensile strength not less than that of the parent material of the rebar. In this study, the main focus is on ordinary rebars, where the qualified Data2 values correspond to the tensile strength of the rebar's parent material. Joints with a tensile strength lower than that of the rebar's parent material are classified as unqualified products in Data2.

3.3 Design and Implementation of CNN-SVM Model

(1) CNN Model Design and Implementation

Firstly, design and train a convolutional neural network (CNN) model suitable for processing images of rebar electric arc pressure welding joints. Based on an analysis of classical CNN architectures, SqueezeNet is chosen as the alternative base model, and recognition training operations are implemented on the MATLAB platform. The specific structure of the CNN model in this paper includes the following parts:

Input layer: Converts each photo sample into a 227*227*3 dimensional image, inputting rebar electric arc pressure welding joint image data.

Convolutional layer: Extracts various indicator feature vectors from the rebar electric arc pressure welding joint image data. The convolutional layer H_i is obtained as follows:

$$H_i = f(H_{i-1} \otimes W_i + b_i)$$

In this context, the weight vector of the i-th layer's convolutional kernel is denoted as W_i ; $\otimes$represents the convolution operation of the kernel with the $i-1$-th layer's feature map; the output of the convolution operation is added to the offset vector $b_i$of the i-th layer, and the sum is inputted into the nonlinear activation function $f\ (x)$, resulting in the i-th layer's feature map H_i.

The third part involves the pooling layer, which learns the crucial features of rebar electric arc pressure welding joint data. The commonly used pooling method in practical applications is max pooling, which selects the maximum value from each part of the input matrix as the corresponding value in the output matrix.

During the model training process, a large amount of rebar welding joint image dataset is used for training, and optimization algorithms such as stochastic gradient descent are applied to adjust the model's parameters, aiming to improve the model's accuracy and generalization ability. A screenshot of the SqueezeNet model in MATLAB is shown in Figure 3.

Fig. 3. SqueezeNet Model Diagram

(2) Feature Extraction and Transformation

After training the CNN model, the trained model will be used to extract and transform features from images of rebar welding joints. By inputting images into the CNN model, high-dimensional feature vectors corresponding to each image can be obtained, reflecting key feature information in the images. To further optimize the representation and extraction effectiveness of the feature vectors, preprocessing operations such as dimensionality reduction and normalization will be applied to ensure that the feature vectors have good interpretability and discriminability. The extracted partial feature vectors after normalization are shown in Table 1.

Table 1. Multi-dimensional Vector Table of Rebar Electric Arc Pressure Welding Joints

Feature / **Sample**	x_1	x_2	x_3	x_4	x_5	⋯
n_1	0.3858	0.4687	0.2819	0.3561	0.4326	⋯
n_2	0.4871	0.6110	0.5467	0.3549	0.4535	⋯
n_3	0.9218	0.4103	0.3522	0.6416	0.4223	⋯
n_4	0.7382	0.8936	0.6446	0.4462	0.5218	⋯
n_5	0.1763	0.0579	0.2161	0.6465	0.1773	⋯
n_6	0.4057	0.3529	0.9434	0.1846	0.1563	⋯
n_7	0.9355	0.8132	0.6871	0.1653	0.4186	⋯
n_8	0.2146	0.0099	0.3591	0.1651	0.1831	⋯

n_j	…	…	…	…	…	…

(3) SVM Model Design and Implementation

Next, the support vector machine (SVM) algorithm will be used to classify the feature vectors extracted by CNN and the results of tensile strength experiments on rebars (qualified, unqualified). This classification training will be implemented using the built-in MATLAB function fitcsvm, and a screenshot of the designed model is shown in Figure 4.

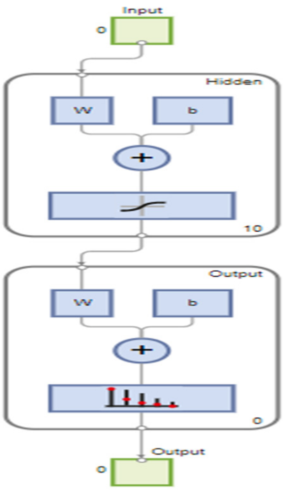

Fig. 4. SVM Model Diagram

In this model, the labels y for rebar electric arc pressure welding joints with tensile strength below the specified value are set to -1, while the labels y for those with tensile strength above the specified value are set to 1. During training, we will adjust the parameters of the SVM model, such as the type of kernel function and penalty parameter, to improve the model's classification performance and generalization ability. Additionally, dimensionality reduction will be applied to the high-dimensional vectors obtained from the CNN model.

4 DISCUSSION OF CNN-SVM MODEL TESTING AND EXPERIMENTAL RESULTS

The testing set of images of electric arc pressure welding joints for rebars is fed into the CNN model to generate apparent feature vectors of these welding joints. These vectors are then inputted into the SVM model for iterative operations. The impact of the number of iterations on various evaluation metrics is observed, with Table 2 listing the predictive accuracy of the model at different iteration numbers, and Table 3 presenting the results of the average values of other evaluation metrics for the model.

Table 2. Model Prediction Accuracy at Different Iteration Counts

Test set	10	50	100	500	1000
1	0.515	0.774	0.827	0.904	0.952
2	0.838	0.877	0.869	0.907	0.958
3	0.602	0.842	0.885	0.863	0.963
4	0.496	0.843	0.846	0.946	0.951
5	0.749	0.715	0.795	0.908	0.972
6	0.603	0.869	0.885	0.922	0.954
7	0.505	0.806	0.853	0.925	0.956
8	0.657	0.814	0.852	0.917	0.962
9	0.613	0.830	0.906	0.944	0.950
10	0.387	0.793	0.887	0.928	0.971

Table 3. Results of Other Evaluation Metrics for the Model at Different Iteration Numbers

Test set	10	50	100	500	1000
Precision	40.62	47.93	62.31	82.35	96.65
Recall	42.37	50.26	57.46	83.27	97.57
F1-Measure	41.25	49.37	64.89	81.49	95.78

It can be observed that after 1000 iterations, comparing the model's predicted results with the actual tensile strength results (qualified, unqualified), the evaluation metrics such as accuracy, precision, recall rate, etc., meet the requirements. This indicates the development of an accurate and reliable CNN-SVM predictive model, suitable for practical assessment and detection of welding joint quality in real-world applications.

5 CONCLUSION

This study constructed a CNN-SVM model to investigate the relationship between apparent features of steel rebar electric arc pressure welding joints and tensile strength. The empirical results validate the good performance of the CNN-SVM model in extracting features from panel data in the construction technology domain and in binary classification tasks. The iteration count of the model indicates fast training speed. Comparing the actual separation situation of the test set with the predicted results shows that the CNN-SVM model has high prediction accuracy, accurately describing the relationship between the apparent features of steel rebar electric arc pressure welding joints and tensile strength. It demonstrates strong applicability and flexibility.

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