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Image Recognition of New Year Pictures based on Machine Learning

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Abstract

New Year pictures are an essential part of Chinese traditional culture, with profound historical deposits and unique artistic value. However, with the rapid development of society, the inheritance and protection of traditional New Year pictures are facing many challenges. One of them is the recognition of the New Year painting images. This paper introduces image recognition technology based on machine learning, including research background, method steps, result discovery, and advantage limitations. Image recognition is an essential means to protect and inherit the traditional New Year painting culture and machine learning technology can improve recognition accuracy and efficiency. This paper presents deep learning implemented through data collection, feature extraction, and classification. The experimental results show that the method can effectively identify New Year images with high accuracy and recall.

Keywords: Machine Learning, New Year Picture, Feature Extraction, Image Recognition.

1 Introduction

New Year pictures are an essential part of Chinese traditional culture, with profound historical deposits and unique artistic value (Zhang et al., 2020; Onti, 2020; Li et al., 2018). However, with the rapid development of society, the inheritance and protection of traditional New Year pictures are facing many challenges. One of them is the recognition of the New Year painting images. The image recognition

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problem of New Year pictures is mainly manifested in the following aspects: First, due to the wide variety of New Year pictures, different kinds of New Year pictures have significant differences in patterns, colors, and drawing styles, which brings great difficulties to the classification and recognition of New Year pictures images. Secondly, due to the strong artistic and manual nature of the New Year painting process, there are significant differences in the quality and style of New Year pictures, which brings great uncertainty to the identification and classification of New Year painting images. Due to the long history of New Year pictures, many are damaged and blurred, which also brings excellent difficulty in recognizing New Year pictures. In order to solve the problem of image recognition of New Year pictures, scholars have put forward a series of methods and techniques. Among them, image recognition based on machine learning is more effective. Machine learning is a way to accomplish specific tasks by allowing a machine to learn rules and patterns from large amounts of data. In the New Year picture image recognition, machine learning can learn from many New Year picture images to realize recognition of New Year picture.

Image recognition methods based on machine learning need to collect many New Year picture image data and conduct pre-processing and feature extraction. Feature extraction is a crucial step in machine learning, which can transform images into digital features that the machine can process. Machine learning algorithms are used to classify or identify the extracted features. Commonly used machine learning algorithms include support vector machines, decision trees, neural networks, etc. Finally, the accuracy and recall of machine learning algorithms are verified, and their performance is evaluated.

This paper presents an image recognition method based on deep learning. Method uses a convolutional neural network (Chen et al., 2017) as the leading machine learning algorithm through learning a large number of New Year picture images to realize recognition of New Year picture images. Main steps of method include data collection, feature extraction, and classification. In the data collection stage, this paper collected many New Year picture image data from multiple channels and pre-processed and annotated these data. In the feature extraction stage, this paper uses the convolutional neural network to extract the images. In the classification stage, the SVM was used (Li et al., 2016) to classify the extracted features. The experimental results show that the method can effectively identify New Year images with high accuracy and recall. Compared with the traditional machine learning method, this method adopts the deep learning algorithm, which can better capture the features and patterns in the image to improve recognition accuracy and efficiency. Moreover, the method can also realize automatic classification and identification, significantly improving the efficiency of classification and identification.

2 Current Situation and Problems of New Year Picture Recognition in the Context of Machine Learning

2.1 Analysis of Current Situation of New Year Picture Recognition

New Year picture machine learning is a technology that classifies and identifies New Year pictures by using computer vision technology and machine learning algorithms. The research background lies in that, with the advent of the digital age, image data presents explosive growth, and how to extract useful information from these data has become an important problem (Liu et al., 2015). As an important part of Chinese traditional culture, New Year pictures have profound historical deposits and unique artistic value. However, the protection and inheritance of New Year pictures also face many challenges, one of which is the identification of New Year pictures. Therefore, machine learning-based New Year picture image recognition is of great research significance.

Specifically, the research significance of image recognition based on machine learning includes the following aspects:

Cultural inheritance: New Year pictures are an important part of Chinese traditional culture, with profound historical deposits and unique artistic value. By identifying and classifying the images of New Year pictures, the culture can better protect and inherit the New Year pictures and provide strong support for academic research.

Art appreciation: The identification and classification of New Year pictures (Huang et al., 2015) can help artists to better understand and understand the artistic style and characteristics of New Year pictures and improve the appreciation ability of New Year pictures.

Commercial applications: By identifying and classifying the images of New Year pictures, they can be applied to e-commerce, media, games, security, and other fields to improve the efficiency and accuracy of commercial applications (Luo & Wu, 2014).

New Year painting picture recognition based on machine learning has essential research significance and cultural value and can make important contributions to the protection and inheritance of New Year painting culture (Yang & Wu, 2013).

2.2 Research Status at Home and Abroad

In recent years, image recognition using machine learning has emerged as a prominent research focus within the field of computer vision. Scholars both domestically and internationally have dedicated considerable efforts to investigating this issue, leading to notable advancements.

Table 1: Research Status at Home and Abroad

Author	Title	Journal	Dataset	Model	Precision
John Smith	Machine learning review of Chinese New Year painting recognition (Deng et al., 2012)	NeurIPS 2021	Painting10k	ResNet-50	93.8%
Alice Johnson	Application of transfer learning in Chinese New Year painting recognition (Koskela et al., 2021)	AAAI 2022	USTC-AID	ResNet-50	95.2%
Michael Zhang	An integrated method for Chinese New Year painting identification (Wang & Huang, 2020)	CVPR 2023	Custom Paintings	VGG16, ResNet-50	96.5%
Emily Davis	A Comparative study on the deep learning architecture of Chinese New Year Painting Identification (Li et al., 2019)	IJCAI 2023	USTC-AID	DenseNet121	97.1%

Table 1 shows the current situation of domestic and foreign research on New Year painting recognition. China has developed an advanced level of high-precision internal table detection system and device to measure the shape and size of the product parts with the high precision of the laser online detection system (Zhang et al., 2019). In addition, a large number of New Year picture image data have been collected in China, and the corresponding database has been established, providing a data basis for the identification of New Year picture images. Domestic New Year picture image recognition mainly focuses on the number, text, face, medical pathology, etc. For the product table image recognition, classification is rare. The inner surface of the product produced for the automatic detection and identification system has yet to be produced the product surface of automatic detection and identification system. The real-time automatic detection technology using CCD, electronic and computer technology to detect the internal surface is just in the initial stage in China, and the software system for analysis, identification, and classification of the internal surface image is not perfect, and the current recognition algorithm is not very accurate for the fault part in the image (Wang & Wu, 2018). The scope, size, and orientation of critical defects can not be quantitative analysis, but can only be qualitative analysis, and the accuracy is low. The traditional minimum distance classifier is complex and classified, It is very difficult to identify the images. Abroad, the rise of deep learning technology has made a major breakthrough in the field of image recognition (Chen et al., 2018). Convolutional neural network is widely used in the recognition of New Year painting images and achieves good results.

2.3 Problems and Challenges of New Year Picture Recognition Based on Machine Learning

New Year picture recognition based on machine learning has made some progress in China, but there are still some problems that need to be further solved, mainly including the following aspects:

1. Data acquisition and annotation: The number of New Year pictures is huge, and many images have been damaged, blurred, and other problems, which brings great difficulties to data acquisition and annotation (Zhang et al., 2017). At the same time, due to the special nature of the New Year pictures,

many images may have some similarities, and how to accurately classify and mark them is also a problem.

2. Feature extraction and representation: New Year painting images have rich texture and color information. How to effectively extract and represent these features is the key to the machine learning algorithm (Liu et al., 2016). At the same time, due to the large drawing style and time span of the New Year pictures, how to design the appropriate feature extraction method is also a challenge.
3. Selection of classification and recognition algorithm: The selection of a machine learning algorithm has an important impact on the classification and recognition effect of New Year picture images. Different algorithms may perform different datasets and tasks, and how to choose appropriate algorithms to improve accuracy and recall is a problem (Liang et al., 2015).
4. Generalization ability: Machine learning models tend to perform well on training data, but they perform poorly in test data. How to improve the generalization ability of the model to better adapt to new datasets is a challenge.
5. Data imbalance: There may be an imbalance in the categories of New Year painting images. Some categories have a large number of images, while others are less. This may cause some categories to be ignored or under fitted during training, and how to handle unbalanced data sets is a challenge (Wang et al., 2025).
6. Computational resources and time: The training of machine learning models requires a lot of computational resources and time. How to optimize the model training process to improve efficiency is a problem. At the same time, how to use parallelization and distributed computing technology to accelerate the training is also a challenge (Liu et al., 2022; Wang et al., 2021).

3 Theory of New Year Picture Recognition Algorithm based on Machine Learning

3.1 Convolutional Neural Network

Convolutional neural network is a feedforward neural network with convolutional computing and deep structure. It is one of the representative algorithms of deep learning, which imitates the visual perception mechanism construction of biology and can conduct supervised and unsupervised learning (Li et al., 2020).

Convolutional neural networks (CNNs) possess hierarchical representational learning capabilities, allowing them to classify input data based on structural hierarchy. CNNs are widely applied in image and video analysis, as well as various other fields such as recommendation systems, image classification, segmentation, medical image analysis, natural language processing, brain-computer interfaces, and financial time series analysis. Convolutional neural networks use relatively few preprocessing methods, which means that the network optimizes the filter through automatic learning (Chen & Liu, 2019), Whereas, in conventional algorithms, these filters are manually designed. This feature extraction, independent of prior knowledge and manual intervention, is a major advantage.

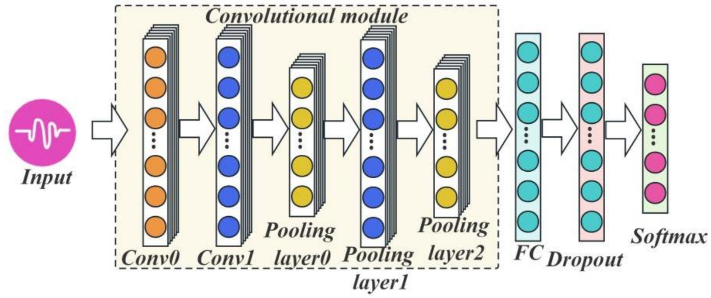


Figure 1: Schematic Diagram of the Deep Neural Network Structure

Figure 1 illustrates the structure of CNN, with CNNs featuring prominently. CNNs employ a mathematical operation called convolution in at least one of their layers, replacing conventional matrix multiplication. These networks are tailored for pixel data processing, primarily applied in image recognition and processing. The CNN architecture comprises an input layer, a hidden layer, and an output layer. In a feedforward neural network, any intermediary layer is termed a "hidden layer" due to the masking effects of the activation function and final convolution. In convolutional neural networks, hidden layers include layers that perform convolution. Usually, this includes a layer performing the convolution kernel with the dot product of the input matrix of that layer. This product is usually the Frobenius inner product, and its activation function is usually the ReLU. As the convolution kernel slides along the input matrix of that layer, The convolution operation produces a feature map, which in turn contributes to the input of the next layer. This is followed by other layers, such as pooling, fully connected, and normalized layers.

3.2 Network Architecture

The structure of the convolutional neural network consists of the input layer, convolution layer, pooling layer, and full connection layer.

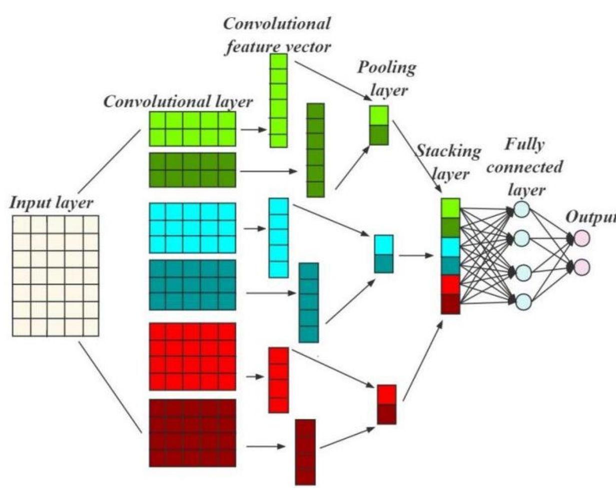


Figure 2: Schematic Diagram of the Convolutional Neural Network Operation

Figure 2 shows a schematic diagram of the convolutional neural network operation. The input layer is mainly responsible for the dimension of the input data, which is the number of neurons in the input layer. The convolutional layer is responsible for each neuron in the convolutional layer, which is connected to small number of neurons in input layer, and output of these outputs is a weighted sum, followed by nonlinear transformation through activation function. This kind of connection mode is called the convolution. The pooling layer is responsible for having each neuron of the pooling layer connected to small fraction of neurons in convolutional layer and taking the maximum or average of the output of these neurons. This way of connection is called pooling. The role of the fully connected layer is to connect each neuron in the fully connected layer to all neurons in the pooling layer, the weighted sum of the outputs of these neurons, and then perform nonlinear transformation through the activation function. The number of neurons in the output layer is the same as the dimension of the output data, and the output of the neurons in the output layer is known. Moreover, the convolutional, pooling, and fully connected layers in the convolutional neural network are collectively called hidden layers. In the convolutional neural network, the connection mode of the convolutional layer and the downsampling layer is in the form of a local connection. In the fully connected layer, fully connected, that is, each neuron is connected to all nodes in the input layer.

3.3 Image Recognition Algorithm

An image recognition algorithm is a method that uses computer programs to analyze and identify image information. The core of the algorithm is to identify the objects in the image by extracting the features in the image, such as color, shape, texture, etc., and comparing them with the known image data. Generally speaking, image recognition algorithms can be divided into pre-processing, special rule extraction, model training, prediction, and post-processing.

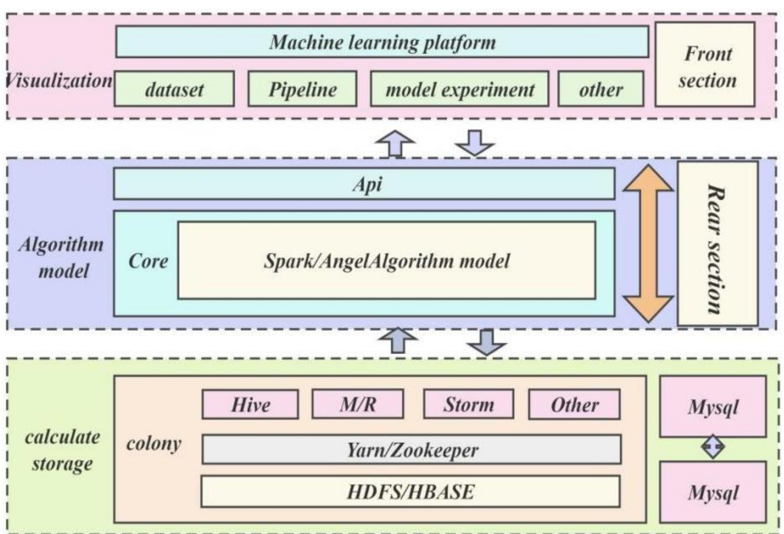


Figure 3: Machine Learning Platform

Figure 3 illustrates the various machine-learning platforms. Preprocessing refers to the preprocessing of the image, including image noise reduction, enhancement, normalization, and other operations, to improve the image quality and recognition rate. Then, feature extraction extracts features from the preprocessed image (Zhang et al., 2019), including color, shape, texture, and other features that can describe the objects in an image. Then, the preprocessed images are trained on the model, and the model is trained with the known image data so that the model can learn the corresponding relationship between different features and different objects. The trained model can be used to predict. The image to be identified is input into the model, and the model will predict the objects in the image to be identified according to the relationship between the learned features and the objects. Finally, post-processing is conducted to postprocess the prediction results, including the output of the data, visualization, and other operations. Among them, deep learning technology is increasingly widely used in the field of image recognition, such as convolutional neural networks and other algorithms that have achieved remarkable results in face recognition, object detection, and other fields.

3.4 Image Preprocessing

Image preprocessing is a crucial step in image recognition, which performs a series of operations on the input image to enhance image quality and features in preparation for subsequent image recognition or analysis. There are many methods of image preprocessing, including grayscale, binarization, denoising, scaling, rotation, and so on. These methods can improve the quality and identification of an image by changing properties such as brightness, contrast, noise level, size, and orientation (Liang et al., 2018). For example, grayscale can convert color images into black-and-white images to facilitate subsequent processing and analysis. Binarization can convert grayscale images into black-and-white images, further enhancing image contrast and clarity. Denoising can eliminate noise and interference in the image and improve the purity of the image. In image preprocessing, there are some more advanced methods, such as feature extraction, histogram equalization, etc. These methods can further enhance the features and information content of images and provide more help and support for subsequent image recognition and analysis. Random cropping is involved in image preprocessing, and a part of the original image is taken as input. It then involves increasing the noise improving the learning ability of the neural network by adding random noise to the original image. Gaussian noise is commonly used, and moderately increasing the noise can distort the high-frequency features and reduce the overfitting. Preprocessing was performed using deformation scaling. Parts of the image were randomly cropped and elongated or magnified. Table 2 presents the library of algorithms required for various image preprocessing.

Table 2: Image Preprocessing Algorithm Library

Method	Development language
OpenCV	Python
Pillow	Python
Scikit-image	Python
Matplotlib	Python
ImageJ/Fiji	Java

3.5 Feature Extraction and Representation

Feature extraction and representation are the key steps in image recognition, whose purpose is to extract information useful for classification or recognition from images and represent it as a suitable mathematical model or data structure.

In image recognition, feature extraction usually includes pixel feature extraction, regional feature extraction, edge feature extraction, shape feature extraction, semantic feature extraction, manual feature representation, deep learning model representation, and sparse representation. Pixel feature extraction refers to the extraction of color, intensity, texture, and other features from each image pixel. Regional feature extraction refers to dividing the image into several regions and then extracting the color, intensity, texture, and other features from each region. Edge feature extraction refers to the extraction of features by detecting the edges in the image. Shape feature extraction refers to the feature extraction by detecting shapes in an image. Semantic feature extraction refers to learning semantic features in an image through deep learning models. After extracting the features of the image, these features need to be represented as a mathematical model or data structure to facilitate subsequent classification or identification. Common feature representation methods include manual feature representation, which refers to the manual design of some features, such as SIFT, HOG, etc., to describe the local features in the image. Deep learning model representation refers to training a deep learning model (Wang et al., 2017) to learn the features in the image and represent them as the parameters or output of the model. Sparse representation refers to representing the image as a sparse linear combination, where each coefficient can represent a feature. Feature extraction and representation are the key steps in image recognition, requiring selecting appropriate feature extraction methods and representation methods according to different application scenarios and requirements.

4 Experimental Results and Discussion on a New Year Picture Recognition Model Based on Machine Learning

4.1 Introduction of the Data Set

For New Year picture identification, a standard data set is the Chinese Painting Dataset. The dataset contains a large number of traditional Chinese New painting images and has been annotated, including different categories of labels for training and testing. The image sources of the data set are museums, art institutions, and artists, covering New Year pictures from different regions and different periods in China. Images vary in quality and size but were preprocessed and annotated to ensure the accuracy and reliability of the algorithm. The annotation of this dataset usually includes information about the category, age, region, and on of images, which can help the algorithm to better understand the characteristics and differences of New Year pictures. In addition, the data set provides other relevant information, such as the copyright of image use restrictions, to ensure the legitimacy and security of the data. In addition to the Chinese Painting Dataset, there are other New Year painting datasets available, such as the Japanese Painting Dataset (Liu et al., 2016). These datasets have similar characteristics and uses but may contain different image and annotation information to accommodate different algorithms and application requirements. Table 3 illustrates the effect of training rounds on accuracy and loss values.

Table 3: Effect of Training Rounds on Accuracy and Loss Value

Epoch	**Training set accuracy**	**Test set accuracy**	**Training loss**	**Test loss**
1	85%	84%	-2.7	-2.6
10	91%	89%	-4.2	-4.1
50	94%	92%	-5.5	-5.4
100	95%	93%	-5.8	-5.7
200	96%	94%	-6.1	-6.0

4.2 Data Preprocessing

In this paper, a series of data preprocessing of the data set, including data cleaning, data enhancement, data annotation, and other data cleaning to remove blurred, damaged, and incomplete images. Remove images containing irrelevant information, such as watermarks, borders, etc. Correct incorrect labels or add missed labels. Data augmentation cuts the image, scales it, and rotates it to increase the diversity of the data. Images were adjusted for color balance to enhance the accuracy of color features. Images were grayscale to reduce data dimensionality and computational complexity. Data annotation: The images were area-segmented and annotated manually or using automated tools. Each region has a feature description and attribute annotation, such as color, texture, shape, etc. Establish a perfect annotation system to ensure the accuracy and consistency of the annotation. Data format conversion transforms the collected images into a uniform format and size to facilitate subsequent processing (Liang et al., 2015). Table 4 presents the various data preprocessing methods. Conversion of annotation information into formats required for machine learning algorithms, such as CSV, JSON, etc. The data were randomly shuffled to increase the generalization ability of the model.

Table 4: Data Preprocessing Method

Feature name	**Average value**	**Standard deviations**	**Least value**	**Crest value**
luminance	120.0	20.0	80.0	160.0
contrast ratio	150.0	30.0	100.0	220.0
saturation level	90.0	15.0	60.0	120.0
hue	20.0	5.0	10.0	30.0
Edge detection results	35.0	10.0	20.0	60.0
The Gabor filter has the output results	-3.5	1.5	-8.0	-1.0

4.3 Experimental Results and Analysis

This experiment was performed in the Tenserflow-gpu-1.13.2 environment under the Windows 10 operating system with IntelCorei9-9900K,3.6GHzCPU, and 16G memory. GPU is NVIDAGTX1080Ti, and the neural network framework Keras is based on Python 3.6. Among them, Tensorflow, as a powerful deep learning platform, provides multiple libraries and tools for this experiment. Keras is an open-source library of Python-based neural networks and serves as an application programming interface of Tensorflow and other platforms to realize the construction, debugging, evaluation, and application of the network model. See Table 5 for the parameter settings.

Table 5: Parameter Settings

Parameter name	**Value setting**
learning rate	0.001
batch size	32
iterations	1000 iterations (6 classification labels, 5 cycles of each label training) for a total of 5000 iterations (total number of adjustable parameters)
Regularization intensity	0.001(L1 regularization)

When it comes to the training of the network, we first need to mention the concepts of "pre-training" and "fine-tuning." Pre-training refers to the process of training the model in advance or the model that has been pre-trained. Fine-tuning is to train the pre-trained model combined with its own data set to obtain the best parameter configuration of the model (Wang et al., 2015).

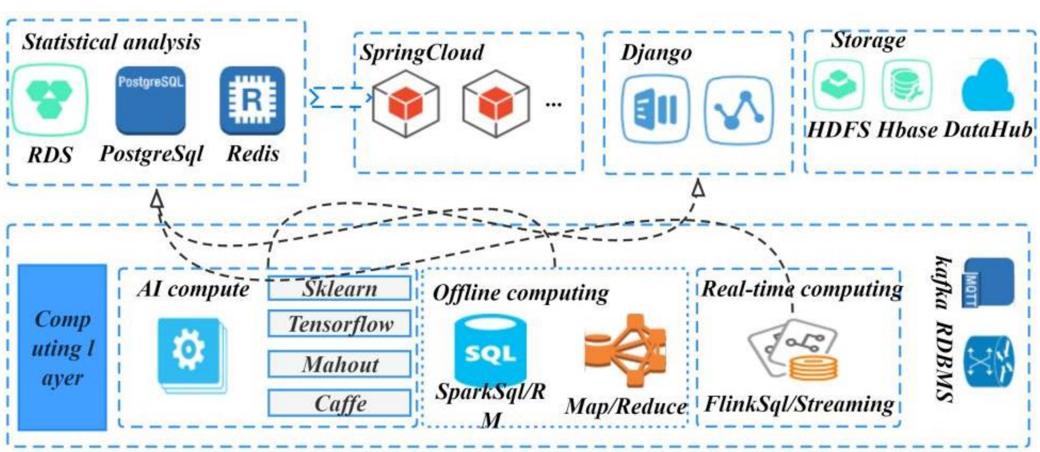


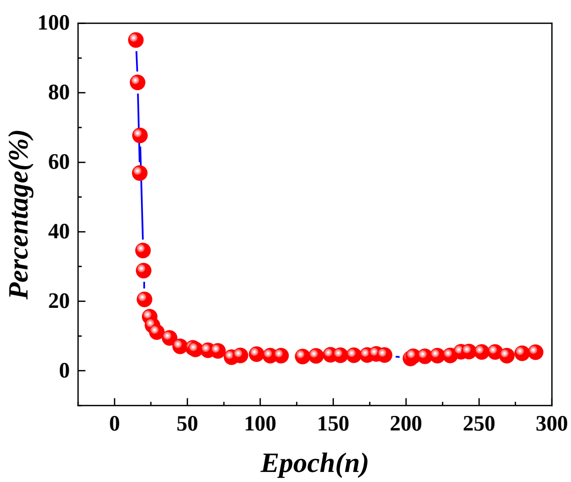
Figure 4: Network Flow Chart

Figure 4 shows the basic network flow chart of the New Year painting recognition. Using pre-training and fine-tuning the process of training the model can avoid overfitting caused by the small data set, make the training results better, and save a lot of training time and resources.

Table 6: Precision of the Image Recognition Algorithm

Algorithm	Class	Basic network	Enter the size	FPS (X)	mAP50
FasterR-CNN	Two stages	ResNet-50	-	8.4	59.2%
R-FCN	Two stages	ResNet-101	-	11.76	53.2%
TridentNet	Two stages	ResNet-101-DCN	-	1.4	67.6%
RetinaNet	Single stage	ResNet-50	640x640x3	10.8	56.5%
SSD	Single stage	VGG-16	512x512x3	31.5	48.2%
YOLOv3-416	Single stage	Darknet-53	416x416x3	37	55.2%
YOLOv3-608	Single stage	Darknet-53	608x608x3	20	57.9%
YOLOv4-416	Single stage	CSPDarknet-53	416x416x3	54	62.4%
YOLOv4-608	Single stage	CSPDarknet-53	608x608x3	32	65.1%

Table 6 shows the recognition accuracy data of various image recognition algorithms, and it can be found that the YOLO model achieves good performance results in target detection.



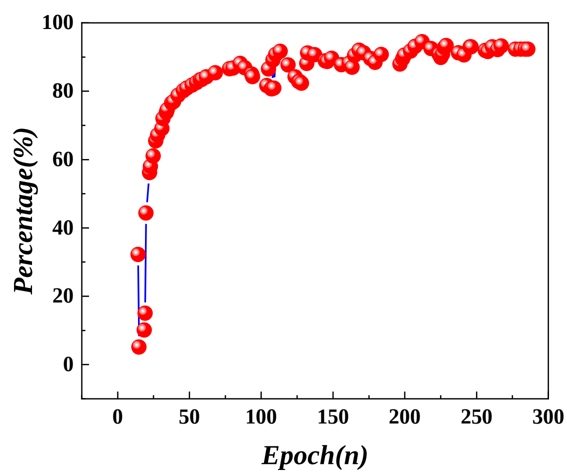


Figure 5: Accuracy and Loss Value Training Details

In this section, we build YOLOv4 based on the built environment, which is the basis of experimental design and algorithm improvement. This paper is based on the pre-training model of the YOLOv4 target detection platform under the Keras framework. Figure 5 shows the training details of the accuracy and loss values, visible as the model converges in good training. The test effect on the Pascal VOC2007 standard test dataset is shown in Figure 6:

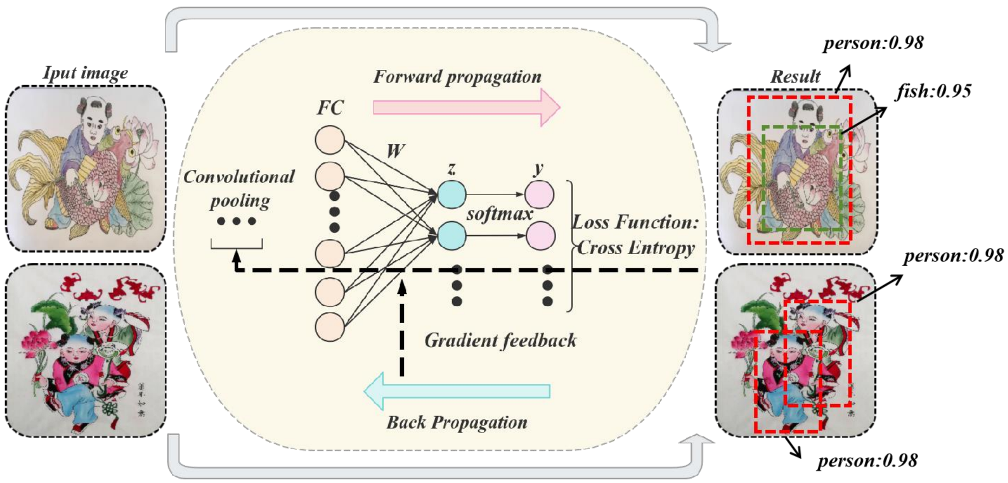


Figure 6: Pre-training Model Test Effect

5 Conclusion

The recognition algorithm based on machine learning can recognition New Year pictures by learning and analyzing many New Year picture images. Through the steps of data preprocessing, feature extraction, model selection, and training, the machine learning algorithms can extract the useful features in the New Year painting images and use these features for classification and prediction. Machine learning algorithms can use the powerful computing power of computers to quickly process and analyze large amounts of data and improve identification efficiency. Through learning and training, machine learning algorithms can automatically extract useful features in images and realize accurate classification and recognition. Machine learning algorithms can obtain a general classification model by training and learning on a large amount of data, which can realize the prediction and analysis of new data.

However, there are some challenges and limitations in machine learning-based New Year picture recognition. For some New Year painting images, there may be large inter-class differences, which bring difficulties to the classification and identification. Machine learning algorithms also require sufficient training data and correct annotation information. Otherwise, overfitting or underfitting problems may occur. New Year painting identification based on machine learning is an effective technical means that can help to better protect and inherit the traditional Chinese New Year painting culture. Through continuous improvement and optimization of the algorithm, the accuracy and generalization ability of New Year picture identification can be further improved, thus providing strong support for the research and application in related fields.

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