# Application scenario analysis based on CNN algorithm

Zhaoxu Guo*

Department of Electronic Science and Engineering, Shandong University, Shandong, 266237, China

* Corresponding Author Email: 202100120129@mail.sdu.edu.cn

**Abstract.** The swift advancement of artificial intelligence technology, facilitated by the rapid progress in science and technology, has significantly enhanced the convenience of our daily lives. As a pivotal model in the realm of deep learning, convolution neural network (CNN) has achieved remarkable feats in various domains such as image recognition, speech recognition, natural language processing, and more. The purpose of this paper is to explore the application of CNN algorithm in different fields, including price prediction, traffic prediction and sentiment text analysis, and summarize its application status, and look forward to the future development trend. While CNN algorithm demonstrates strong performance in these areas, its limitations hinder significant contributions in certain fields. Nevertheless, it is anticipated that with continued advancements in science and technology, CNN algorithm will exhibit commendable performance across diverse domains. This study projects CNN's future development trends and gives an overview of the technology's current application status in a number of sectors, making it a useful resource for relevant applications and research.

**Keywords:** Deep learning, Convolution neural network, Price prediction, Traffic prediction, Sentiment text analysis.

## 1. Introduction

Artificial intelligence has emerged as the primary driver behind modern science and technology due to the swift advancement of information technology. Convolution Neural Network (CNN), as an important branch of deep learning, has shown excellent performance in many fields due to its unique network structure and powerful feature learning ability. CNN initially excelled in the field of image recognition, effectively extracting spatial features in images, providing strong support for image classification, object detection and other tasks [1]. In recent years, its application field has been expanding, not only limited to image processing, but also to natural language processing, speech recognition, medical diagnosis, financial prediction, and other fields. In these fields, CNN has shown strong feature extraction ability and efficient learning efficiency, providing new perspectives and solutions for solving complex problems.

This paper analyzes the CNN algorithm theoretically, discussing its key components, such as convolution, pooling, fully connected layers, and activation functions. By explaining how each component affects overall network performance and interacts, we can better understand CNN's efficient feature extraction and classification tasks. The paper also delves into CNN's achievements in price prediction, traffic, and emotional text analysis. For example, in the financial field, stock price prediction based on CNN model has achieved some success. In the aspect of traffic management, the use of CNN for vehicle detection and tracking also shows good results. In addition, in the aspect of emotional text analysis, CNN is widely used in emotion classification and opinion mining. Finally, the paper discusses CNN's challenges in practical application and its future development direction. Despite its excellent performance and progress, CNN still faces issues like insufficient model interpretability and large data demand. Future CNN technology can be improved to serve various industries more deeply by enhancing model architecture, computational efficiency, and anti-attack defense. This paper aims to provide a reference for related research and promote further exploration and innovation in this field.

## 2. Basic theoretical analysis of CNN algorithm

CNN is a special neural network structure that is inspired by the hierarchical structure of biological vision systems. CNN locally perceives the input signal through convolution operation, and uses the weight sharing strategy to reduce the network parameters, so as to achieve efficient feature extraction and classification of the input data [2]. The CNN framework is composed of various layers, such as the input layer, the convolution layer, the pooling layer, and the output layer. The former handles feature extraction, while the latter is used to reduce data dimensions. The fully connected layer is also responsible for mapping the features of the framework to the sample marker area. The CNN framework's workflow is composed of two phases: forward propagation and the back-propagation. The first stage involves the passing of the input data by layer through the various convolution layers and pooling layers. The latter stage involves the classification result. During the back-propagation phase, the network optimization is carried out according to the difference between the classification outcomes and the true label. The CNN structure diagram is shown in Figure 1 below.

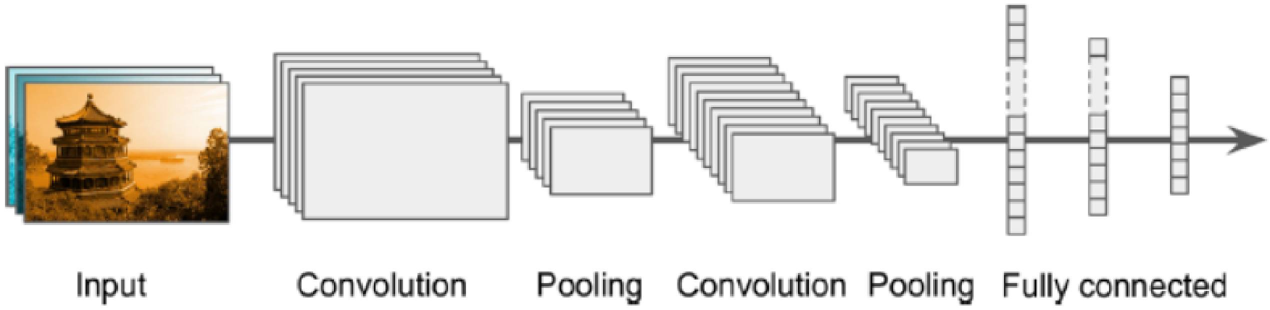


**Fig. 1** CNN structure [2]

### 2.1. Convolution layer

The convolution layer plays a critical role in feature extraction within machine learning models, particularly for image recognition tasks. This layer utilizes filters, also known as convolution kernels or feature detectors, which slide over input data and compute dot products to create feature maps. The depth of these aligns with the quantity of filters utilized in the convolution layer. Each filter is capable of learning distinct features like edges, textures, and more. During training, the weights of the convolution kernels continually adjust to capture various feature patterns effectively. In the context of machine learning image recognition, the process does not involve recognizing the entire image simultaneously. Instead, it focuses on identifying individual features within the image initially. Subsequently, higher-level operations are performed on these localized features to derive comprehensive global information.

### 2.2. Pooling layer

The pooling layer typically follows the convolution layer, aiming to shrink the spatial dimensions of the feature map. This action simplifies the model's complexity and enhances the translation invariance of the model. The most common pooling operations are maximum pooling and average pooling. Maximum pooling selects the maximum value as output within the pooling window, which helps to preserve the main features and reduce the size of the feature map, while improving the robustness of the network to translation invariance. Average pooling takes the average value within the pooling window. Pooled layers are often used interchangeably with convolution layers, and by reducing the size of feature maps, pooled layers can reduce the computational and memory requirements of the model and help prevent overfitting. The pooling operation can also improve the position invariance of features, that is, for the same feature appearing in different positions, the pooling operation can make the position information of the feature less sensitive, thus enhancing the model's generalization capacity. However, excessive pooling can lead to information loss, so the size and step size of the pooling operation need to be carefully selected when designing the network.

### 2.3. Fully connected layer

The fully connected layer typically sits between the convolution layer and the output layer and is used to map the features extracted by the convolution layer to the output class. Every neuron within the fully connected layer establishes connections with all neurons in the preceding layer, hence the designation "fully connected". This connection method enables the fully connected layer to learn complex nonlinear relationships, thereby improving the expressive ability of the model. In image classification tasks, the output of a fully connected layer is usually normalized by a softmax function to produce a probability distribution for each category. Fully connected layers usually have a large number of parameters, which can easily lead to overfitting, so in practical applications, regularization techniques or dropout layers may be used to reduce the risk of overfitting. The regularization technique can minimize the model's complexity by penalizing the parameters of the model, while the dropout layer randomly discards a part of the neurons during the training process to reduce the dependency between neurons, thus enhancing the model's ability to generalize.

### 2.4. Activation Functions

Activation functions are used in CNN to introduce nonlinear, allowing the network to learn complex features and patterns. Popular activation functions comprise Rectified Linear Unit (ReLU), Sigmoid, and Tanh. ReLU stands out as one of the most frequently employed activation functions, which returns the input value in the positive part and zero in the negative part, with the advantage of simple calculations and constant derivatives. The Sigmoid function compresses the input value between 0 and 1 and is suitable for the output layer of binary classification problems. The Tanh function compresses the input value between -1 and 1 and is typically used for hidden layers. These activation functions all help to increase the nonlinear expression ability of the network, thereby improving the learning ability and fitting ability of the model. Choosing the right activation function depends on the specific task and network structure.

## 3. Application field analysis

### 3.1. Price Forecast

In utilizing CNN for price forecasting, our initial step involves gathering historical price data and structuring it into time series format to uphold data quality and integrity. Then the price time series is converted into a format suitable for CNN model processing, usually the sliding window method is used to convert the time series into the form of images, that is, the continuous price series is converted into two-dimensional images, in which time is taken as one dimension and price as another dimension. Then we design and structure the CNN model for price prediction, and divide the data set into training set, validation set and test set. Finally, the training set is utilized to train the designed model, while during the training process, the validation set serves to assess the model's performance on unseen data, so as to timely adjust the structure and parameters of the model and avoid overfitting or underfitting. The evaluation results of the validation set can guide the optimization of the model and the selection of the best parameters. Test sets are used to evaluate the model's ability to generalize in the real world when the model has been trained and tuned. The samples in the test set represent data that the model has not encountered during training, so the evaluation results of the test set can more truly reflect the performance of the model in practical application.

Cao et al. proposed a CNN-based stock price prediction model. Firstly, the collected data were de-noised by wavelet threshold to remove interference signals, then the CNN model was employed to extract and choose features from the preprocessed data, and finally the LSTM model was used for prediction. By forecasting the trained WD-CNN-LSTM model and comparing it with the CNN-LSTM model, LSTM model and GRU model, they found that the prediction accuracy of the WD-CNN-LSTM model has been greatly improved [3]. Yang proposed a CNN-based gold futures price prediction model. Firstly, the data were preprocessed, such as missing value processing and normalization processing, and then the CNN model was used for in-depth feature extraction of the data. Then the BiGRU model was used to analyze the extracted data, and finally the gold futures price prediction could be realized. After comparing CNN-BiGRU model with BPNN model, LSTM model, GRU model, BiGRU model and CNN-GRU model, the author observed that, when compared to the four fundamental models, the combined model demonstrated superior prediction accuracy, with the CNN-BiGRU model producing predicted values closest to the actual ones [4]. He proposed a carbon emission rights trading price prediction model based on CNN-LSTM model. The combined model consisted of convolution layer, maximum pooling layer, LSTM layer and fully connected layer. The data were normalized and divided into data sets at first, and then convolved by sliding window training mechanism. Then the trained model is tested using the data of the test set, and the CNN-LSTM model that can predict the carbon price is finally obtained. After comparing the trained CNN-LSTM model with LSTM model, LSTM-ARIMA model and SVR model, it has been observed that CNN-LSTM model has the highest prediction accuracy [5].

### 3.2. Traffic Prediction

The method of using CNN model for traffic forecasting is similar to that of price forecasting, except that the collected data becomes traffic data, such as vehicle flow, speed, road conditions, etc. Using CNN to process image data captured by traffic surveillance cameras can realize real-time prediction of traffic flow. By training the model to learn the spatio-temporal characteristics of traffic flow, it can predict the traffic flow in the future for a certain period of time and provide decision support for traffic management. Bao et al suggested a forecasting approach of short-cycle traffic flow at traffic intersections based on CNN-ARIMA. Firstly, Z-Scores were normalized for collected traffic flow data and according to 8: The ratio of 2 is partitioned into training set and test set, and then the constructed CNN-ARIMA model is trained and tested, and the model is continuously optimized, and finally the traffic flow at the traffic intersection is predicted. After comparing the trained CNN-ARIMA model with LSTM model and MA model, they discovered that the prediction accuracy of all three models increased when the number of vehicle samples was low. However, as the sample size increased, the prediction accuracy of the CNN-ARIMA model slightly decreased, yet remained notably superior to that of the other two models [6].

Traffic accidents often lead to significant changes in road conditions, such as vehicle congestion, accident sites, etc. Using CNN to analyze traffic monitoring images in real time, abnormal situations can be found in time, such as vehicle collision, pedestrian fall, etc., so as to respond quickly and deal with traffic accidents. Shi et al. proposed an urban road traffic event detection algorithm based on CNN. Firstly, traffic accident data, peak period data and peak period data were collected as data sets, and the training set comprised 70% of the data, while the test set encompassed 30%. Then, this data set was employed for training the CNN model, and the optimal parameters were found by testing and optimizing the model. Finally, the road results are obtained through the output layer of the model. After comparing with BP algorithm and two CNN control groups with different parameters, it is found that the comprehensive effect of the CNN algorithm is the best. The CNN algorithm demonstrates superior capability in identifying the spatio-temporal characteristics of traffic flow, showcasing enhanced recognition functionality compared to traditional neural networks [7].

Traffic sign is an important part of road traffic, which is of great significance to the driver's driving safety. CNN can train the model to recognize a variety of traffic signs, including ban signs, warning signs, indicating signs, etc. This helps to assist drivers to better understand the road rules and improve driving safety. Tian et al. presented a traffic sign recognition model based on the integration of CNN and Bagging. First, the traffic sign data set was processed by image expansion and enhancement, and the data set was split into training set, verification set and test set, and then the CNN model was trained with the expanded training set data. During the training phase, Bagging integration is employed to enhance the generalization capability of an individual model. Subsequently, the test set data is utilized to fine-tune the trained model, culminating in its deployment for predicting traffic signs. After comparing the improved CNN-Bagging model with the CNN model, ResNet50 model and VGG16 model, the enhanced CNN-Bagging model exhibits notably superior prediction accuracy compared to the other three models [8].

### 3.3. Emotional text analysis

Traditional sentiment text analysis methods are mainly based on hand-extracted features and machine learning algorithms. However, this approach requires a lot of feature engineering and domain knowledge, and its performance can be limited for complex textual data. In recent years, deep learning, especially CNN algorithm, has achieved significant advancements in natural language processing, offering a novel approach to addressing emotional text analysis challenges. In affective text analysis, CNNS can automatically learn feature representations of text data without complex feature engineering. The input to the CNN is usually a series of word vectors that can be obtained through pre-trained word embedding models such as Word2Vec, GloVe, etc. Then, CNN extracts the local and global features in the text through convolution and pooling operations, and finally outputs the emotion classification results through the full connection layer and softmax function. Xu et al. proposed an applied research on sentiment classification of comment text based on BERT and CNN. First, web crawler technology was used to collect text data, then data cleaning was carried out to achieve text de-noising, and finally data annotation was carried out to obtain data set. Then data was passed through BERT pre-training model, and the output vector was trained and optimized by CNN model. Finally, the sentiment analysis of comment text is realized. After comparing with Word2Vec-CNN model and BERT model, the author finds that the accuracy and emotion classification accuracy of BERT-CNN model are improved [9]. Jin et al. proposed a logistics comment emotion analysis model based on BilSTm-CNN-Multiheadattention-dropout. First, the product comment data of an e-commerce platform is collected using crawler technology, and then the comment data is processed by BiLSTM model for dimensionality reduction. Feature extraction was then carried out through the CNN model, then the MultiHeadAttention mechanism was used to extend the model's ability to focus on different locations, and finally the Dropout mechanism was used to solve the overfitting problem. The author compares the combined model with CNN model, BiLSTM model, Attention-CNN model, Attention-BiLSTM model and Attention-Bilstm-CNN model, and finds that the prediction accuracy of the combined model is higher than that of other models [10].

## 4. Challenges and prospects

Despite the commendable performance of CNN models across numerous domains, they still encounter several challenges.

(1) CNN model training demands a significant amount of data, but there are many fields with different data quality and insufficient data, so the lack of large-scale data to train CNN model is a major challenge for the application of CNN model.

(2) Because CNN is a deep learning model with a very complex structure, the prediction results are usually difficult to explain. Therefore, it is difficult for the prediction results of CNN to play a role in some fields requiring in-depth explanation, such as medical diagnosis and judicial fields.

(3) Data characteristics and task requirements in different fields are different, which requires CNN model to have good generalization ability. However, many current CNN models perform well on certain data sets, but significantly degrade on other data sets, which limits the practical application of the models.

Although CNN is currently facing many challenges, we can combine different models according to various shortcomings of CNN model, which can process information more comprehensively and help us solve problems. To address the problem of data diversity and imbalance, future CNN models need to develop adaptive learning algorithms, which can dynamically adjust the model structure and parameters according to the data distribution and task requirements, and enhance the resilience and generalization capacity of the model. We can also develop techniques and methods that can explain the decision-making process of CNN, which will help to improve the interpretability and credibility of CNN model, so as to facilitate the application of CNN model in more fields. I believe that with the development of science and technology and the in-depth study of machine learning, these problems will be solved, and the future CNN model will be better applied in various fields and provide strong support for the development of various fields.

## 5. Conclusion

This paper discusses the theory and application of convolution neural network (CNN), especially in price prediction, traffic prediction and sentiment text analysis. In the theory part, the structure of CNN is described, including convolution layer, pooling layer, fully connected layer, and activation function. In the application part, this paper analyzes the application of CNN in price prediction, traffic prediction and emotion text analysis. However, while CNN has excelled in many areas, it still faces some challenges. For example, the CNN model requires a large amount of data to train, and in some areas, the data quality is uneven and the amount of data is insufficient. In addition, the predictions of CNN models are often difficult to interpret, which can be a problem in areas that require in-depth interpretation, such as medical diagnosis and justice. Finally, the data characteristics and task requirements of different fields are different, which requires CNN model to have good generalization ability. However, many existing CNN models perform well on specific data sets but significantly degrade on others, which limits the practical application of the models. In order to solve these problems, future CNN models need to develop adaptive learning algorithms, which can dynamically adjust model structure and parameters according to data distribution and task requirements, and improve model robustness and generalization ability. In addition, it is necessary to develop techniques and methods that can explain the decision-making process of CNN, so as to improve the interpretability and credibility of the model, so as to promote the application of CNN model in more fields. In general, this paper makes a comprehensive discussion on the theory and application of CNN, and shows the successful application of CNN in many fields. At the same time, this paper also points out the challenges faced by CNN and the future development direction, which provides a valuable reference for future research.

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