International Journal of Multiphysics
Volume 18, No. 3, 2024
ISSN: 1750-9548

Study on Express Parcels Classification Encoding Method based on Deep Convolutional Neural Network

Linlin Wang*
Zhongshan Torch Polytechnic, No.60, Zhongshangang Avenue, Torch Development Zone, Zhongshan, Guangdong, China
*Corresponding Author.

Abstract

With the rapid development of express delivery business, a large number of express parcels require accurate classification by coding to achieve fast sorting and delivery. In response to the differentiated and precise delivery needs of express parcels, this paper studies the method of dividing express parcels priorities using deep neural networks. By establishing a deep neural network model and training, different express parcels priorities are divided using direct information of express parcels. Neural network training and testing data sample simulation generation, with sample data generation strategies designed based on actual logistics and distribution needs. The structure and configuration parameters of the deep neural network were ultimately determined through training and testing. The priority of parcels is obtained through deep neural networks, and the priority is encoded together with direct information of express parcels for fast sorting and delivery, which providing a reference for classification and coding methods for differentiated and precise delivery of express parcels.

Keywords: Express sorting, classification coding, priority; deep neural networks.

1. Introduction

With the rapid development of express delivery business, whether fast sorting of express parcels can be achieved determines the delivery efficiency of express parcels, and fast sorting of express parcels depends on the classification and coding method of express parcels [1,2]. The classification and coding of express parcels is an important task in the information management of express parcels. The design of classification and coding for express parcels should start from the whole process, scientifically and reasonably classify express parcels, develop adaptive and standardized coding rules, and standardize the description of express parcels attributes[3,4].

In the existing express parcels coding methods, effective codes can be obtained by directly coding based on information such as the source, delivery destination, type, quantity, and delivery time limit of the express parcels. By establishing rules for numerical coding, effective codes can be obtained. However, when there are a large number of parcels that cannot meet the delivery schedule, there is a separate agreement on the delivery time, or there are important parcels that require priority delivery, the above coding method cannot reflect the priority level of express parcels. Therefore, it is necessary to establish priority allocation principles and prioritize different parcels based on their direct information. With the emergence and development of artificial intelligence methods, it is feasible to use such algorithms to prioritize express parcels [5-14].

In this paper, a deep neural network method for prioritizing express parcels was studied. A network model was established to prioritize different express parcels based on their direct information, and the priority was encoded together with the direct information to achieve accurate delivery of express parcels.

2. Classification and coding method for express parcels

In order to achieve differentiated and precise delivery of express parcels, different types of express parcels are classified and coded according to the following coding process.

(1) Encode the source, destination, type, quantity, and delivery time limit in the direct information of the express parcels;

(2) Based on the source, destination, type, quantity, and delivery time limit of the express delivery, a deep neural network model is established to determine the priority of the express parcels;

(3) Add the priority code for the express parcels, and the final classification code is obtained.

The above process is completed sequentially, and the final classification code of the express parcels is provided for fast sorting. Among them, the priority of express parcels is crucial and is the core link in the classification and coding of express parcels. Priority is given through the established deep neural network.

In order to achieve fast sorting of express parcels, it is necessary to classify and code the express parcels. The information used for classification coding includes direct information such as the source, destination, type, quantity, and delivery time limit of the express parcels, as well as derived information such as the priority of express parcels derived from these direct information.

The direct information of express parcels can be directly assigned a value code through digital coding methods, while the derivative information of express parcels needs to be analyzed and obtained from the direct information of express parcels by establishing a predictive model.

Neural network methods are highly effective prediction methods that can accomplish the above tasks, which includes Back Propagation (BP) neural network model, Support Vector Machine (SVM) network model, and deep neural network model.

1) BP neural network model

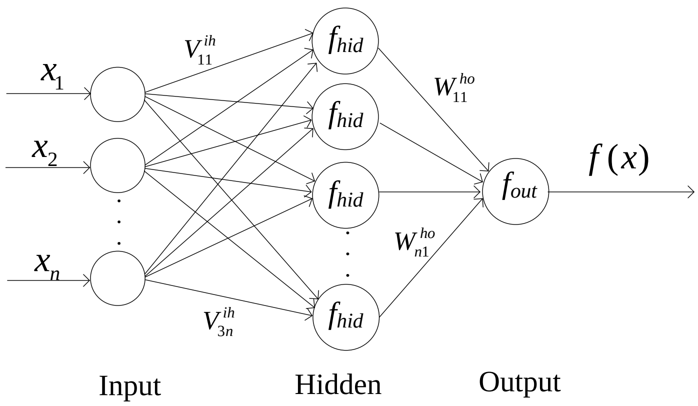

Figure 1 BP model

The structure of the BP neural network is shown in Figure 1, which consists of an input layer, a hidden layer, and an output layer. The input data of the input layer includes direct information such as the source, destination, type, quantity, and delivery time limit of the express parcels. The data dimension is large, and there may be multiple layers of hidden layers in the architecture. Similarly, the number of nodes will also be large. The actual number of selected nodes should be determined based on the training situation.

Preprocess the direct information such as the source, destination, type, quantity, and delivery time of express parcels in the training set data stream and represent it in the form of matrix vectors. Divide each set of data streams into 1, 2, 3, 4, and 5 priorities as output. Train the network by adjusting the number of nodes, network layers, error range, activation function, etc. After the model is trained, input the test set data stream into the model to determine its priority. The encoding program executes the next operation based on priority.

2) SVM network model

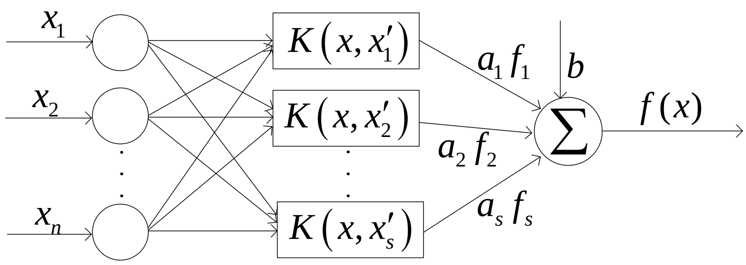

Figure 2 SVM model

The SVM model as shown in Figure 2, has the same input and output as the BP model. The RBF neural network with a Gaussian kernel in the middle layer can be trained by adjusting the bound C of the Lagrange multiplier, error range ε, and parameter σ to optimize the model. In the data processing process, each input is transformed into a matrix vector that can be recognized by the network, and priority is assigned to each training data stream based on the priority of express parcels. After the network model is trained, for each input data stream, the model can quickly calculate the priority of this data stream based on the learning situation, and the coding program executes the next operation based on the priority situation.

3) Deep neural network model

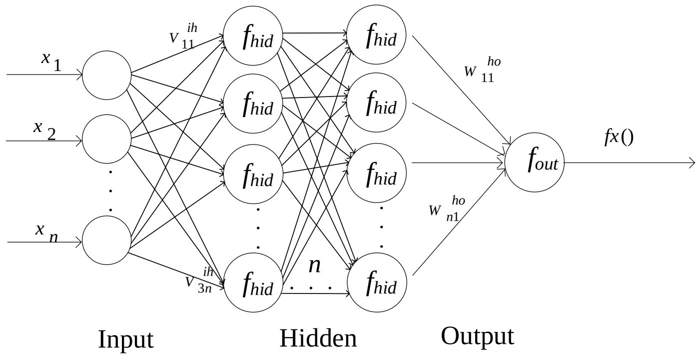

Figure 3 Deep neural network model

The structure of a deep neural network is shown in Figure 3, which consists of an input layer, a hidden layer, and an output layer. The input data of the input layer includes direct information such as the source, destination, type, quantity, and delivery time limit of the express parcels. The data dimension is large, and a deep neural network model needs to be constructed for training. There may be dozens of hidden layers in the architecture, and the number of nodes will also be large. The actual number of selected nodes should be determined based on the training situation. The principle for determining the number of hidden layers and nodes above is to ensure that the model is as stable as possible, and also to ensure its learning ability for new data. In the data processing process, each input is transformed into a matrix vector that can be recognized by the network, and priority is assigned to each training data stream based on the priority of express parcels. After the network model is trained, for each input data stream, the model can quickly calculate the priority of this data stream based on the learning situation, and the encoding program executes the next operation based on the priority situation.

Through analysis and comparison, a deep neural network model is selected to classify the priority of express parcels in this paper, and based on this, the encoding of express delivery types is implemented.

3. Model Modeling and Training

3.1 Modeling of deep neural network model

Firstly, a model based on deep neural networks is established, using the collected direct information data stream of express parcels as the input for the training unit. Each data stream is divided into different levels based on division principle. The level classification of the data stream is used as the output to train the established deep neural network model.

After training, the deep neural network model was tested. A new data stream is selected and input into the deep neural network model to determine whether the priority matches the calibrated priority, completing the deep neural network testing task. The input-output relationship of deep neural network is shown in Figure 4.

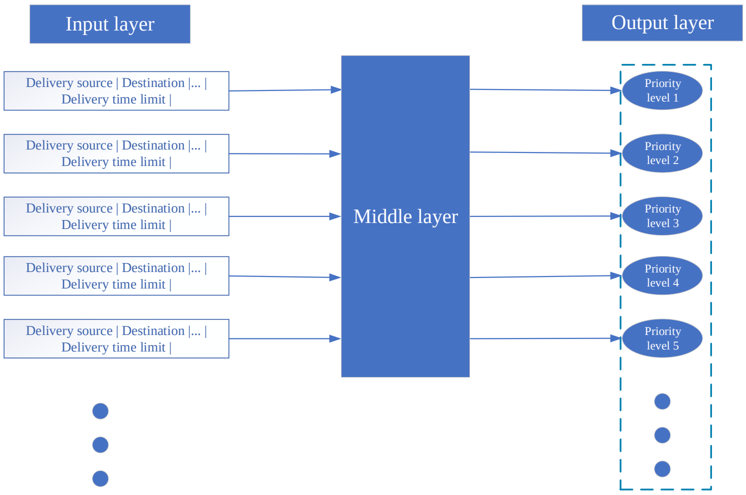

Figure 4 The input-output relationship of deep neural network

The structure of the deep convolutional neural network established based on the input-output relationship of the deep neural network is shown in Figure 5.

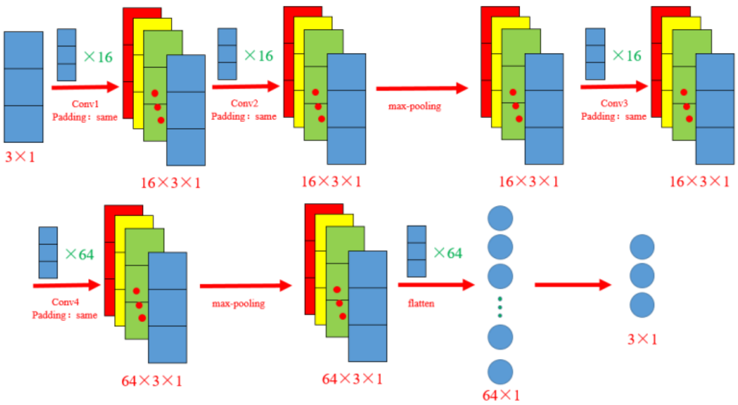

Figure 5 The structure of the deep convolutional neural network established

The initial input of the established neural network model is a 3×1 one-dimensional matrix. After multiple convolutions and max pooling, a total of 64 3×1 matrices can be obtained. Then, a fully connected layer is used to expand the matrix to obtain a 64×1 matrix. By adding a soft-max layer, the corresponding material delivery priority (3×1 matrix) can be obtained. Based on this idea, the network can be optimized and trained by adding convolutional and pooling layers.

3.2 Training and testing data generation

Based on the direct information of the express parcels, such as source, destination, type, quantity, and delivery time, the priority of express parcels is divided into three levels: level 1, level 2, and level 3. The priority levels of these three levels are sequentially reduced. Due to the inability of the data on the list of express parcels to be directly input into the computer network for training, custom encoding is applied to the direct information of express parcels, and some data types are selected and converted into corresponding numbers. Based on the actual situation of the verification environment, three parameters (type, quantity, and delivery time) are planned to be selected as inputs for the convolutional neural network, and three output priorities are set for training. Due to the lack of a large amount of data for training in the early stages of development, sample data is generated based on the actual situation. The rules for generating training and testing sample data are shown in Figure 6.

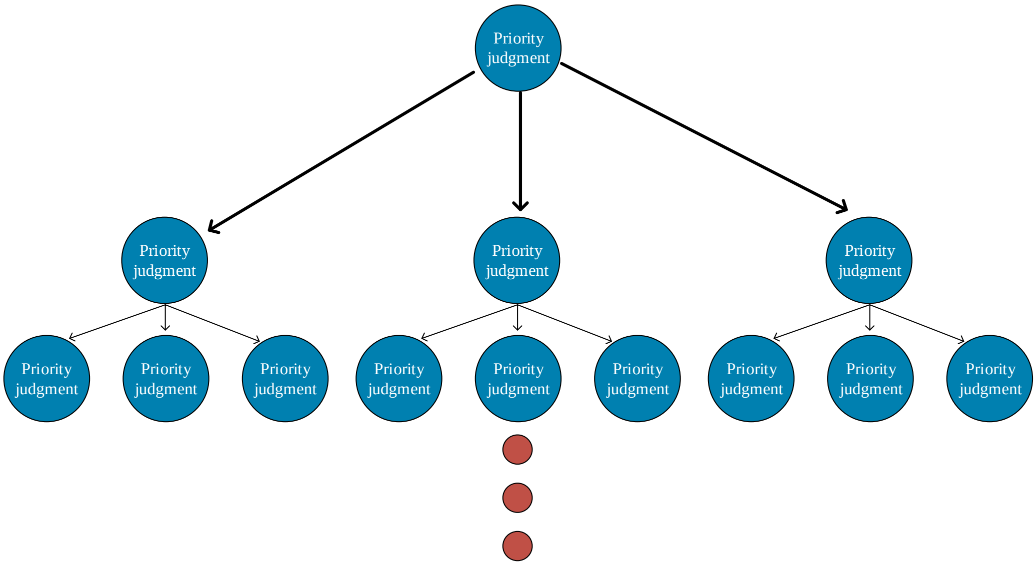

Figure 6 Rules for generating training and testing sample data

According to the rules for generating training and testing sample data, the first five layers of state judgment can be defined as source, destination, type, quantity, and delivery time limit to identify the network. In practice, the above data generation graph can be adjusted according to the classification and filtering rules of express parcels. According to the actual situation of the verification environment, the source and destination is not used as input data for network training.

The first level of state judgment in the data generation graph is defined as the type of express parcels, which is divided into three levels: 1, 2, and 3 based on the different types of express parcels. The express parcels type is assigned from 01 to 10 based on the direct information of the express parcels. The level allocation principle is that 01-03 is level 1, 04-06 is level 2, and 07-10 is level 3.

The second level of status judgment is defined as the number of parcels, which is divided into three levels too: 1, 2, and 3 based on different parcels. According to the direct information of parcels, the number of parcels is allocated into ten numbers from 01 to 10. The principle of level allocation is that 01-03 is level 1, 04-06 is level 2, and 07-10 is level 3.

The third layer is the delivery time limit for express parcels, which is divided into three levels: 1, 2, and 3 based on the delivery time limit. According to the direct information of the express parcels, the delivery time limit is assigned into three types: 2, 4, and 5, corresponding to three levels: 1, 2, and 3. Based on the above data generation principles, parameters can be continuously added as training inputs according to the complexity of actual delivery situations. After the three-layer judgment is completed, 1 to 27 numerical levels are obtained, and then the above numerical levels are merged and divided. The priority of 1-9 is merged into level 1, the priority of 10-18 is merged into level 2, and the priority of 19-27 is merged into level 3.

The defined data is used as the input layer of the neural network model, and the target priority is used as the output layer of the neural network. The established deep convolutional neural network is trained. Among them, the target priority is a numerical assignment code based on the actual delivery order arranged according to the type, quantity, and delivery time limit of the actual parcels. For example, if the parcels type is 01, the parcels quantity is 01, and the delivery time limit is 2, the priority of express parcels is 1. The generated partial data is shown in Table 1.

According to the data generation rules, 1000 sets of sample data are generated, and training and testing sets are randomly generated in an 8:2 ratio to obtain 800 sets of training set data and 200 sets of testing set data.

Table 1 Generated data

Type	quantity	Time limit	Priority
03	02	2	1
05	04	4	1
07	09	5	3
07	07	4	2
10	07	5	3
04	09	4	2
06	07	2	1
09	04	4	2
01	09	4	1
04	07	5	2
06	02	5	1
07	08	5	3
05	07	4	2

3.3 Model training and testing

The training sample set is input into the established neural network model to output prediction priority, and the model is trained based on the difference between prediction priority and calibration priority. During the training process, the conv1+conv2+max pooling layer is used as a unit, and the number of layers after conv3 is frozen as a post unit.

By adding the number of pre units for layer optimization, the layers are set to 1 and 2 respectively, and the activation functions are all Relu functions. Comparative experiments are conducted, with epochs set to 60 and batch_size set to 1. The comparison of network training results is shown in Table 2.

Table 2 Training results of layer 1 and layer 2 network

Layer number	Accuracy of test results	Time consumption (s)
1	100%	3
2	100%	4

Compared to the 1-layer network structure, the 2-layer network structure takes 4 seconds to reach the prediction accuracy for the first time. The reason is that an additional convolutional and pooling layer structure is added to the training network, which increases the calculation time. In order to reduce time complexity, T network structure with 1 layer is selected while maintaining the same accuracy.

After the neural network model is trained, the test sample set is input into the trained network model for verification. If the test results are qualified, the model is established. If the test results are not qualified, the network will be optimized by adjusting the network structure, parameters, error accuracy, etc., and finally the network model will achieve the desired output. The test samples were input into the neural network model for testing, and the test results are shown in Figure 7.

The neural network model established after final training and testing consists of an input layer, followed by the addition of two convolutional layers conv1d_1 and conv1d_2, as well as a max pooling layer max pooling, and then, the structure of adding two convolutional layers conv1d_3 and conv1d_4 with a max pooling layer continues, with an output data expanded into a fully connected layer to form a perceptron, and the last layer is the output layer, outputting priority categories. Among them, the padding of the convolutional layer and pooling layer is set to same because the input data has fewer dimensions.

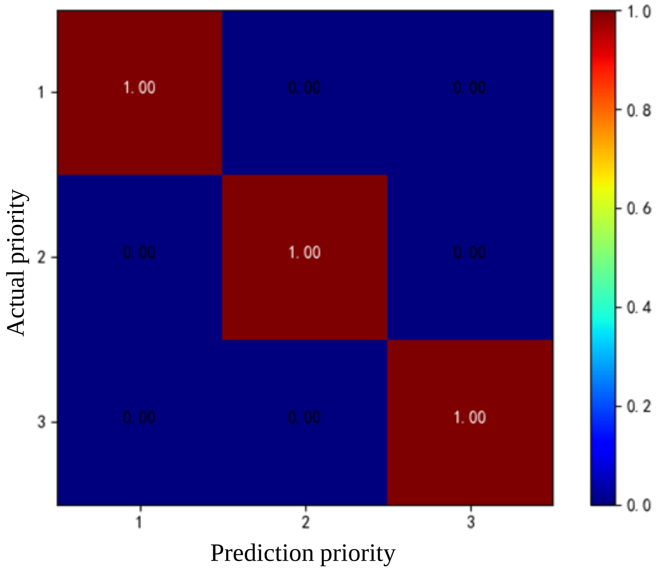

Figure 7 Test results of the established neural network model

4. Results

After testing the sample data, it was found that the accuracy of the test results reached 100%, fully meeting the requirements. Considering that the rule formulation was relatively clear when constructing the dataset, the test results performed well. In actual working conditions, when faced with actual express delivery needs, the priority output results given by the neural network model may differ from the generated data test results, but it can meet the usage requirements. After the above neural network training and testing steps, the neural network model based on deep learning algorithms has been trained and tested.

By help of this deep neural network model, different express parcels priorities are divided using direct information of express parcels, and the priority is encoded together with direct information of express parcels, providing a reference for classification and coding methods for differentiated and precise delivery of express parcels.

5. Discussion

In response to the situation where there are a large number of express parcels that cannot meet the delivery schedule, there is a separate agreement on the delivery time, or there are important express parcels that require priority delivery, the method of dividing express parcels priorities using deep neural networks is studied, and The digital priority code generated based on direct information of express parcels is used for final encoding of express parcels. By establishing a deep neural network model, training and testing, the direct information of express parcels is used to achieve the division of different express delivery priorities, and the priority is encoded together with the direct information of express parcels, providing a classification and coding method reference for differentiated and accurate delivery of express delivery.

References

[1] Wang R. Research on Digital Encoding Design for Efficient Address Identification of Express Delivery Manifests. National Business News, 2016 (28): 3. DOI: 10.3969/j.issn.1009-5292.2016.28.011

[2] Peng L, Zhu D. Material coding design. Standard Science, 2013 (2): 3 DOI: 10.3969/j.issn.1674-5698.2013.02.015

[3] Gao Y, Xue X, Liu H. Research on Classification and Coding of Digital Management Information for Materials in Electric Power Engineering Projects. Engineering Construction and Design, 2023 (16): 84-87

[4] Yao Q. Application research on material identification and tracking management in the SMT industry . Shanghai Jiao Tong University, 2024. DOI: CNKI: CDMD: 21015.027173

[5] Jia A, Deng C. Driving fatigue prediction model based on BP neural network and its effectiveness analysis. Agricultural Equipment and Vehicle Engineering, 2024 (002): 062

[6] Wang L, Zhang Y, Li J. BP Neural Network Based SubPixel Mapping Method. Springer Berlin Heidelberg, 2006 .DOI:10.1007/978-3-540-37258-5_87.

[7] Lu Y, Yu J, Zhu X, et al. A lightweight rice leaf disease identification model based on convolutional neural networks. Jiangsu Agricultural Journal, 2024 (002): 040

[8] Schirrmeister RT, Gemein L, Eggensperger K ,et al. Deep learning with convolutional neural networks for decoding and visualization of EEG pathology. Human Brain Mapping, 2017, 38(11):5391-5420. DOI:10.1002/hbm.23730.

[9] Lotte F, Congedo M, Anatole Lécuyer, et al. A review of classification algorithms for EEG-based brain–computer interfaces. Journal of Neural Engineering, 2007, 4(2).DOI:10.1088/1741-2560/4/2/R01.

[10] Cang R, Ren MY. Deep Network-Based Feature Extraction and Reconstruction of Complex Material Microstructures//ASME 2016 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference. 2016. DOI:10.1115/DETC2016-59404.

[11] Gu L. Design of a multi-dimensional similar big data classification system based on SVM. Information and Computer, 2024 (002): 036

[12] Chen Y , Zhou X S , Huang T S .One-class SVM for learning in image retrieval//Proceedings 2001 International Conference on Image Processing (Cat. No.01CH37205).IEEE, 2001. DOI:10.1109/ICIP.2001.958946.

[13] Ge Y. Research on Key Technologies of Material Distribution in Discrete Manufacturing Workshop Based on Intelligent Perception Network. Nanjing University of Aeronautics and Astronautics, 2019.

[14] Shi H, Niu L. Research and Implementation of Material Distribution Method Based on Intelligent Perception Network// 2021 IEEE International Conference on Advances in Electrical Engineering and Computer Applications (AEECA). IEEE, 2021.