

## Retraction

# Retracted: Path Optimization of Enterprise Network Innovation Performance Management Based on Deep Learning and Internet of Things

### Journal of Mathematics

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Manipulated or compromised peer review

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

### References

- [1] P. Xiong, "Path Optimization of Enterprise Network Innovation Performance Management Based on Deep Learning and Internet of Things," *Journal of Mathematics*, vol. 2022, Article ID 4932439, 10 pages, 2022.

## Research Article

# Path Optimization of Enterprise Network Innovation Performance Management Based on Deep Learning and Internet of Things

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In today's global competition environment with rapid changes in market and technology, it is more and more difficult for enterprises to fully grasp the latest knowledge and learn all the technologies by relying on their own strength. It is particularly important for enterprises to establish a network relationship of a certain intensity with other external entities (upstream and downstream enterprises, peer enterprises, scientific research institutions, government departments, financial institutions, and other organizations) for their technological learning and improvement of technological innovation performance. From different perspectives, the academic circles have confirmed that the strength of network relationship does have an impact on the technological innovation performance of enterprises. This paper will explore the measurement scale of technology learning cost, and from the basic perspective of technology learning cost, deeply explore and analyze how enterprise technology innovation performance is affected by the strength of enterprise network relationship. This paper argues that the strength of network relationship can affect the cost of technology learning and therefore the performance of technology innovation. The main contents of this study include the following. (1) Through the collation and review of the related theories of network relationship strength, technological learning cost and technological innovation performance, and the existing research results, the theoretical model of this study is established, and the theoretical assumptions of this study are put forward. (2) A presurvey is carried out first, and the data collected from the presurvey are used to test the reliability and validity of the scale of this study, and the appropriate measurement scales for the strength of network relationship, technology learning cost, and technology innovation performance are determined. (3) Adopt the method of regression analysis combined with the SME method, to verify this paper builds the theoretical model, and further clarify the network relation intensity, technology acquisition cost, and cost of technological learning all dimensions and performance of technological innovation and network strength, technological learning mechanism between cost, and performance of technological innovation.

## 1. Introduction

In today's society, the market is changing rapidly and technology is changing rapidly. Technological learning becomes a potential source for enterprises to build competitive advantages [1]. Due to the limitation of the enterprise's own resources, it is difficult for the enterprise to fully grasp the latest technical knowledge. Embedded social networks can provide effective channels for enterprises to obtain timely and accurate information for technological learning and can directly provide knowledge resources, information, and

complementary resources for technological learning [2]. Both resource-based view and knowledge-based view point out that only by continuously acquiring knowledge resources such as information from the external environment for continuous technical learning can enterprises maintain stable development in the increasingly competitive market. It can be seen from this that enterprise technology learning is closely related to enterprise social network. The process of technology learning needs to consume a certain amount of resources; it is inevitable to produce learning costs. From a certain point of view, the cost of technology learning is

caused by the existence of various obstacles affecting learning, and the cost of overcoming various obstacles is the cost of technology learning. Before the technical learning has reached the fixed goal, the cost of learning directly determines whether the technical learning can be carried out, continued and successful. The cost of technology learning has also become an important issue in the research and practice of technology management. Therefore, whether an enterprise can quickly obtain timely and effective resources from the complex and dynamic social network to overcome the obstacles in technology learning is the key to its success in technology learning. The network relationship of different intensity has different influences on the acquisition, transmission, and absorption of information in the enterprise technology learning, and the cost of technology learning and the performance of technology innovation are closely related to the acquisition, transmission, and absorption of information. Some scholars believe that strong network relationships are conducive to enterprises' access to self-beneficial information and knowledge, which is conducive to enterprises' technical learning. On the contrary, some scholars believe that the network knowledge flow with strong relationship is more frequent, which increases the cost of knowledge transfer and is not conducive to the technological learning of enterprises. Therefore, it is very important for enterprises to maintain a reasonable strength of relationship with social network members.

When studying the relationship between the strength of network relationship and enterprise technological innovation performance, many scholars analyze and study from the angle of knowledge transfer and have obtained rich results. In [3], trust and reciprocity among network members with strong relationships can reduce the level of conflicts between organizations and produce a mechanism for solving problems together, so it is conducive to information transfer between organizations. Andrew C Inkpen pointed out that, in the weak relationship network, the trust between individuals is relatively low and the psychological distance is relatively far, so individuals will show strong self-protection behavior in the process of cooperation, which will obviously limit the transfer and sharing of knowledge. Reagans and McEvily studied the influence of network relationship strength of knowledge source on its tacit knowledge transfer behavior from the perspective of knowledge source. By studying the tacit knowledge transfer behavior among employees within a R&D company, they found that the degree to which a knowledge sender sends knowledge is affected by the knowledge reticence and the strength of network relationship. In addition, compared with the dimension of social network structure, the strength of network relationship is able to reduce the obstacles for knowledge source to transmit knowledge [4]. In [5], it was found that strong network relationship is conducive to the improvement of knowledge transmission and knowledge absorption capacity of the two sides of tacit knowledge transfer, so the more frequent, extensive, and in-depth knowledge sharing and communication between the two sides of knowledge transfer will be strengthened. Schmidt and Roth [6] found through the investigation of pharmaceutical enterprises in

Zhejiang, China, that strong Wanfang Data 5 network relationship can play the role of enterprise information channel, and the high-quality information transmitted in this channel is conducive to promoting the transfer of complex knowledge between enterprises, thus significantly improving the technological innovation capability of enterprises. Gu et al. [7] found that the efficiency of interorganizational cooperation is closely related to the strength of interorganizational relations. On the one hand, the higher the intensity, the higher the interaction frequency and the degree of trust, which is conducive to the tacit knowledge transfer between organizations. On the other hand, overdependence on strong relationships may restrict enterprises to a relatively closed network with limited information resources and make it difficult for enterprises to access and obtain information resources outside the closed network, thus restricting the innovation path of enterprises. In [8], the study showed that, compared with networks with weak relationships, the knowledge acquired by groups with close relationships is often highly similar. Therefore, tacit knowledge transfer between closely related groups is not conducive to the development of the group's own innovation activities, and the weak relationship is more conducive to improving the innovation performance than the strong relationship. Huang et al. [9] discussed the influence of cluster network relationship strength on technological innovation from the perspective of inner and outer cluster relationship of core enterprises. They believe that, for an enterprise, the resources needed to maintain internal and external relationships are limited, so the strength of internal and external relationships shows a negative relationship. The strong network relationship is beneficial to the knowledge exchange both inside and outside the cluster, but the weak external relationship provides heterogeneous knowledge and is beneficial to the technological innovation of enterprises. Therefore, there is an inverted U-shaped relationship between the strength of cluster network relationship and technological innovation.

At present, the passive device fingerprint access authentication algorithm generally adopts the method based on shallow feature learning. In [10], protocol types are used as device features to construct the device fingerprint matrix. Based on the feature process of [10], [11] adopts algorithms such as KNN, AdaBoost, and SVM to realize the device access authentication based on passive device fingerprint. The above methods are all shallow feature representation methods. Gupta and Govindarajan [12] proposed a passive fingerprint method that could identify different wireless drivers on network connected devices. McEvily and Zaheer [13] proposed an IOT device identification method that supported a variety of communication connection technologies (including WiFi, ZigBee, Ethernet, and Z-Wave), and tested it on the dataset of communication devices, with good test results. Zander and Kogut [14] proposed a method to identify the type of devices connected to the IP network to realize the identification of device types. Cumming and Teng [3] designed an Internet of Things scanner to identify devices by visualizing media access control (MAC) layer traffic, but regular use to identify devices and compare their

fingerprints to the baseline would increase the processing load. In [4–6], the IAT value is used as the unique feature of the device, and three-layer perceptron is used to implement device access authentication based on the similarity measurement method. The research results show that the IAT value can be used to identify device types and individual devices, but the IAT value for device access authentication depends on a large number of data packets, which will inevitably lead to a long time for device identification in real application scenarios. In view of the above problems, this paper applies the deep learning model to the IoT access authentication scenario based on passive device fingerprint and proposes a deep learning-based IoT device access authentication method. This method uses the bidirectional LSTM (BiLSTM) model to extract features from passive device fingerprints and realize identification of IoT devices. Compared with the traditional LSTM model, the BiLSTM model takes into account the future information and has better recognition effect.

## 2. Innovation Performance Management

The bucket is divided into mobile terminal, sensor module, wireless communication module, power module, and motor drive module according to functions. The sensor module is equivalent to the “eyes” and “ears” of the smart trash can. It uses infrared sensors, temperature sensors, and pressure sensors, respectively. It is mainly responsible for the security detection part of the smart trash can and provides more human services for the intelligent delivery. The wireless communication module runs through the communication system of the entire intelligent trash can, and the data communication between the mobile terminal and the SCM control is realized through the wireless communication module. The functions of the IoT service system include processing and analyzing the monitoring data transmitted by each sensor on the garbage can, and the server automatically builds the database of relevant monitoring data. Multiple kinds of data collected in all areas can be analyzed, the real-time status of smart garbage cans can be distinguished by mobile terminal monitoring, and the sanitation staff can be reminded to clean the garbage buckets in a timely and effective manner. The overall system design and application of soft and hard can be a different garbage intelligent delivery, from the source to reduce the burden of cleaning personnel. The specific operation process is shown in Figure 1.

**2.1. Software Design.** Considering that if the image recognition module is loaded on hardware, the overall power consumption of the garbage classification system will be greatly increased, and it is difficult to update and upgrade the garbage photo library in the future; the focus will be on the mobile terminal. At present, there are two major mobile platforms, IOS and Android, and each has a huge ecosystem. If we want to adapt them, respectively, the development cost and the increase of the weekly period will bring a great burden to the project. The microchannel small program is

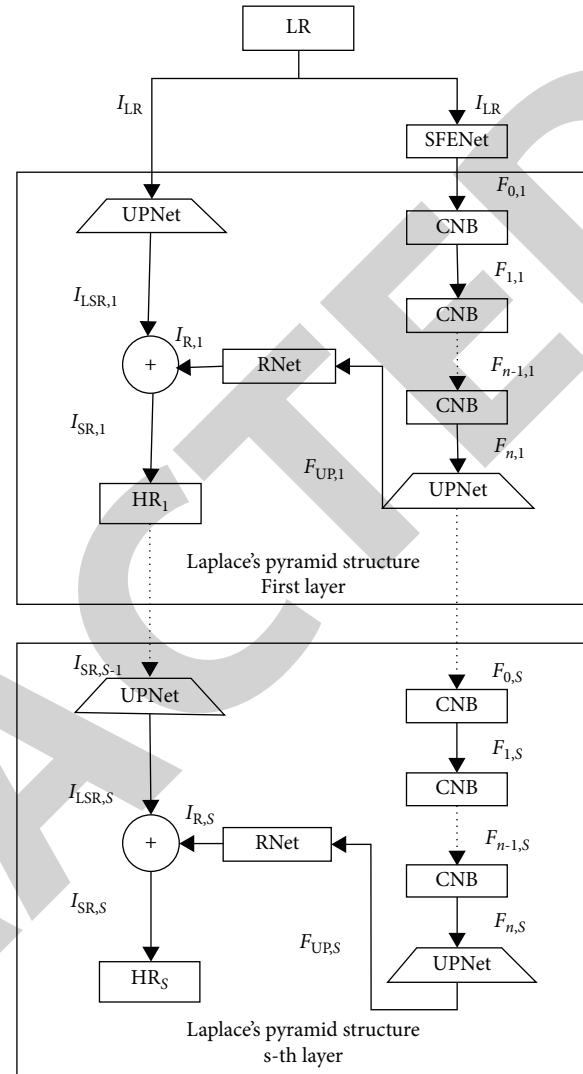


FIGURE 1: LCN structure.

lightweight, convenient, spanning two platforms, and a large user base. Based on the above considerations, this paper developed a microchannel small program, named intelligent garbage classification system. The small program was developed by WeChat developer tools at the front end, and the Flash framework with simple core and easy to extend was used to build the server side. The deep learning model deployed in the server was trained on the existing garbage classification dataset using SSD algorithm.

### 2.1.1. Specific Functions.

- (i) Click the search box at the top to enter the search interface. Enter the name of the garbage in the search box, and the corresponding garbage will pop up. Click the garbage with the name similar to the garbage, and click to view the corresponding category of the garbage.
- (ii) Click the “Location” button at the top to enter the location interface. The location interface calls the

API of Tencent map, and users can find the location of the nearest intelligent classification trash can and within a certain distance can be automatically connected with the intelligent classification trash can Bluetooth.

- (iii) Click the “Camera Recognition” button in the middle to enter the camera interface. In the camera interface, the user can take photos through the mobile phone camera and upload the photos to the server side. The server side will recognize and process the pictures and return to multiple possible categories of items. The user can jump to the corresponding garbage category of the item by selecting and clicking the category of the actual item. If it is connected to the intelligent classification garbage can at this time, the signal will be transmitted to the garbage bucket, and the corresponding category garbage bucket cover will open automatically.
- (iv) Click the “Classification” button in the bottom navigation bar to enter the garbage classification guide interface. The garbage classification guide interface contains the introduction of different types of garbage, as well as the classification of common garbage.
- (v) Click the “Quiz” button on the side to enter the garbage sorting and answering interface. Ten different kinds of garbage will be randomly given on the garbage sorting answer interface. Users can choose the corresponding garbage type, and the correct answer will be given according to the number of correct answers.

*2.2. Hardware Design.* The specific hardware modules of the intelligent trash cans are divided into SCM main control board, overflow automatic monitoring module, temperature detection module, voice prompt module, steering gear drive module, wireless communication module, and power module. The main control module of this design plays the logical control role in the whole hardware system. It is the most important part of the whole system and the core of the whole system [15].

- (i) **Solar power:** the smart trash can is powered by installed solar batteries and uses batteries to store excess electrical energy obtained on sunny days for use on rainy days. The use of solar battery power not only solves the difficulty of long-distance power supply in the street but also saves energy and protects the local environment. In addition, solar cells made with current technology have a very long life.
- (ii) **Voice prompt module:** the module uses infrared sensing technology, which is a technology that uses infrared ray and pyroelectric principle to sense human activity information. When people enter the sensing range, it can accurately identify and detect passively sensing human activity information. The sensor can be rotated 60° to the left and right, easily

changing different sensing areas. Furthermore, the TF card equipped with MP3 voice and the battery are inserted into the corresponding position of the trash can, and the indicator light will flash once when the status switch is switched to ON. If there is no operation, the product will be in the waiting state, and the voice will be played when the induction is triggered. When a resident walks near a trash can with a trash bag, the voice prompts automatically play. For example, “it is everyone’s responsibility to protect the environment. Please throw the rubbish into the dustbin.”

- (iii) **The automatic detection module overflows:** the module uses infrared probes and pressure sensors. When the garbage accumulation in the garbage bin reaches a certain height or the weight of the garbage reaches a certain weight, the system will prohibit the lid of the garbage bin from opening and display a red light to indicate that the garbage bin is full. Among them, infrared wave is sent to the garbage box by installing an infrared probe. When the garbage in the garbage bin is full, the garbage blocks the reflected infrared ray reception. At this time, the garbage can be considered to be full and reported to the cloud platform so that the cleaning personnel can be arranged to deal with it in time. The pressure sensor is used to monitor the amount of garbage in the garbage box in real time. When the amount of garbage reaches the preset value, the system will achieve the preset effect. It is forbidden to open the dustbin lid and show the red light. The design of the module prevents environmental pollution caused by garbage overflow, and it does not need the cleaning personnel to repeatedly check whether the garbage is full, which saves a lot of manpower and material resources.
- (iv) **Temperature detection module:** the module uses a temperature sensor that sends information to the server when the temperature in the litter exceeds the preset value and is used to monitor the temperature of the garbage box to prevent high temperature and fire phenomenon.
- (v) **Wireless communication module:** in the design, the data communication between the mobile terminal and the microcontroller is established by the Bluetooth technology in wireless communication. Bluetooth communication range is large, the cost is low, and its use is targeted, so it is very convenient to set up the relevant data communication, while other wireless communication is not suitable for either the cost or the APP device required for setting up the communication. In addition, the Bluetooth device used in the design has less power consumption, which requires less power consumption in similar communication devices. Because of the limitation of each module of the trash can, it is more reasonable to use the Bluetooth equipment.

- (vi) **Steering gear drive module:** steering gear drive module through steering gear rotation simulates the dustbin switch cover. Its working principle is roughly as follows. First of all, the steering gear itself has a control signal and the driving signal is generated by the single chip microcomputer, to achieve the movement of different angles of rotation and to provide effective guarantee for the accurate lid opening of the trash can. This module is based on Bluetooth wireless communication to receive information from the upper computer, so as to determine which part of the steering gear to control the switch cover of the garbage bucket. It is controlled by the high and low level of the I/O output of the single chip microcomputer, and it drives the starting and stopping and reversing of the steering gear through the on-off of the control bridge arm. Then, the system determines which door is always open when no one is operating, and quickly feedback the information to the main control board. The main control board receives the information and controls the work of the steering gear. The steering gear rotates at a certain angle to complete the closing of the bucket cover, and the module basically completes the opening and closing of the trash can cover.

### 3. Deep Learning Algorithm Model

Super-resolution image reconstruction refers to the technology of converting existing low-resolution images into high-resolution images by means of software algorithms by means of signal processing and image processing [1]. Because high-resolution images have higher pixel density, they have richer texture features and sharper edge features, providing a better visual experience for users. The essence of super-resolution image reconstruction task is to produce corresponding images in high-resolution space as accurately as possible on the premise of providing low-resolution spatial data. In this paper, a deep learning-based approach is used to reconstruct high-resolution images by learning the mapping relationship between low-resolution space and high-resolution space. A Clique network super-resolution image reconstruction algorithm based on Laplace pyramid is the proposed structure, LCN. In order to maximize the communication between the convolution layers, more features are extracted. The Clique Block in CliqueNet was introduced into SR network, and the CliqueNet was further improved. The improved structure was named CNB as the building module of LCN. There are forward and feedback connections between any two convolution layers in the same CNB, and the information between layers is updated alternately so that the information flow and feedback mechanism can be maximized, and the connections between layers are denser. At the same time, the Laplace pyramid structure is used to gradually reconstruct the high-resolution image, and the reconstruction results are optimized step by step. Residual learning is applied to the network to reduce network parameters and avoid gradient explosion. From the

experimental results, the super-resolution image reconstruction algorithm proposed in this paper produces good subjective and objective reconstruction results, especially in the reconstruction of edge and line.

*3.1. The Clique Network of Laplacian Pyramid Structure.* In this paper, a group network of Laplacian pyramid structure is proposed. Laplace pyramid structure has been widely used in image aliasing, texture synthesis, edge sensing and filtering, semantic segmentation, and other fields with good results. Therefore, the network in this paper adopts the Laplace pyramid structure, which can gradually optimize the reconstruction results by the way of gradual reconstruction of high-resolution images. At the same time, the improved group network CNB is used as the building module of Laplacian pyramid structure. Currently, CliqueNet is only used for advanced computer vision tasks (for example, object recognition). The network can maximize the communication between the convolution layers and extract more features. Therefore, this paper improves it and introduces it into SR network.

*3.1.1. Overall Network Structure.* The overall structure of the network is shown in Figure 1.  $I_{LR}$  is taken as the input of the system, and  $I_{LR,S}$  is taken as the output of the s-level reconstruction network of the Laplace pyramid structure. Then,  $I_{LR,S}$  can be obtained by the following formula:

$$I_{LR,S} = H_{LCN,S}(I_{LR,S-1}), \quad (1)$$

where  $H_{LCN,S}$  represents the process of obtaining the s-level high-resolution image HR of Laplace pyramid, which can be a composite function. More details on LCN are given in Section 3.1.2.

*3.1.2. Loss Function.* As can be seen from Figure 1, ILR is the input low-resolution image, and it is assumed that  $\theta$  is the set of network parameters to be optimized. Then, the goal of the network is to learn the mapping function F and generate the estimation image of the real high-resolution image:

$$\hat{I}_{SR} = f(I_{LR}; \theta). \quad (2)$$

Let IR and S be the residual image of the sth level of the Laplace pyramid, ILSR and S are the low-resolution image directly magnified by the sth level of the Laplace pyramid, and ISR and S are the high-resolution image of the sth level of the Laplace pyramid. Then, at level S of the Laplace pyramid, the expected output high-resolution image can be modeled as follows:

$$I_{SR,S} = I_{ILSR,S} + I_{R,S}. \quad (3)$$

The loss function of the network can be obtained as follows:

$$L(I_{SR}, I_{SR}; \theta) = \frac{1}{N} \sum_{i=1}^N \sum_{s=1}^L \rho(I_{SR,S}^{(i)} - I_{SR,S}^{(i)}), \quad (4)$$

where  $\rho$  is the Charbonnier function,  $N$  is the number of training samples in each batch, and  $L$  is the series of the pyramid.  $I_{LR,S}$  is obtained by using the corresponding number of bi-cubic subsamples of real high-resolution images at different levels of the Laplace pyramid. According to formulas (2)–(4), each level has its loss function, and the total loss is the sum of the losses at all levels. This multiloss structure makes the residual of different response levels need to be deeply supervised and guide network training, so the network can predict the residual images of different levels and generate multiscale output images. Therefore, if the model in this paper is trained with an 8x magnification model, the super-resolution results of 2x magnification, 4x magnification, and 8x magnification can be obtained in a feedforward. This feature can be applied to resource-sensitive devices such as mobile devices or network applications.

**3.2. Laplacian Pyramid Structure.** In this paper, the network adopts Laplacian pyramid structure. As shown in Figure 1, each level of the pyramid structure contains two processes: feature extraction and image reconstruction. Because the low-resolution image and the high-resolution image share a lot of information, only the residual is studied in this paper. In the process of feature extraction, the residual image is obtained, and in the process of image reconstruction, the residual image is added to the low resolution image matrix to obtain the high-resolution image. Thus, the network parameters are reduced, which are advantageous to the gradient transmission and prevents the gradient from disappearing or exploding.

**3.2.1. Feature Extraction.** For a very deep network, it is difficult and impractical to directly output all the features extracted from each convolutional layer in LR space. Therefore, in this paper, CNB structure is designed as the building block of Laplacian pyramid structure so that more features can be extracted. In each level of the Laplace pyramid, feature extraction is composed of CNB building module, UPNet, and RNet. The input goes through the CNB building module, upsampling network, and residual extraction network in order to predict the residual image at the current pyramid level. The output of each upsampling network is connected to two different layers, one of which is used to extract residual images at the pyramid level, and the other is used as the input for feature extraction at the next level of the pyramid.

Taking  $F_{0,S}$  as the  $s$ -level input of the Laplace pyramid, assuming that there are  $n$  CNB building modules in the  $s$ -level of the Laplace pyramid structure, the output of the  $N$ TH CNB building module,  $F_{n,S}$ , can be obtained by the following formula:

$$F_{n,S} = \begin{cases} H_{\text{CNB},n}(H_{\text{CNB},n-1}(\dots H_{\text{SFE}})) & \text{if } S == 1 \\ H_{\text{CNB},n}(H_{\text{CNB},n-1}(\dots F_{0,S})) & \text{otherwise} \end{cases}, \quad (5)$$

where  $H_{\text{CNB},n}$  represents the feature extraction of the  $N$ TH CNB building module, which can be a composite function. More details on the CNB building blocks are given in Section 2.4.  $H_{\text{SFE}}$  represents the convolution operation of feature extraction performed by the network input  $I_{LR}$  through the shallow feature extraction network (SFENet).

After obtaining the detailed features extracted by the CNB building module, the upsampling network is used to carry out the upsampling. Then, the upsampling feature  $F_{UP,S}$ , obtained at the  $s$ -level of the image can be obtained by the following formula:

$$F_{UP,S} = H_{UP}(F_{n,S}), \quad (6)$$

where  $H_{UP}()$  represents the convolution operation. Input  $F_{UP,S}$  is the detailed feature obtained after  $n$  CNB building modules in the  $S$  level.

After the upsampling feature is obtained, the residual image is obtained by using the residual extraction network. Then, the residual image  $IR$  and  $S$  generated in the  $S$  level of the Laplace pyramid can be obtained by the following formula (7): where  $H_R()$  represents the convolution operation. The input is the feature  $F_{UP,S}$  obtained by the pyramid  $s$ -level image through the upsampling network. So far, the  $s$ -level feature extraction of Laplace pyramid is completed:

$$I_{RS} = H_RF_{UP,S}. \quad (7)$$

**3.2.2. Image Reconstruction.** In each level of Laplace pyramid, image reconstruction is mainly composed of UPNet and residual fusion. The input first passes through the upsampling network, and then, the upsampling magnified low-resolution image and the residual image obtained from the feature extraction branch are summed in pixels to produce the output image with high resolution. At the same time, the output high-resolution image is used as the input of the next pyramid to reconstruct the high-resolution image of the next pyramid.

At the pyramid  $S(S \geq 1)$ , when  $S = 1$ , the upsampling network is used to upsample the input low-resolution image. In addition, the upsampling network is used to upsample the high-resolution images generated at  $S-1$  level. The amplified low-resolution image obtained after upsampling can be obtained by the following formula:

$$I_{LSR,S} = \begin{cases} H_{UP}(I_{LR}), & \text{if } S == 1 \\ H_{UP}(I_{SR,S-1}), & \text{otherwise} \end{cases}, \quad (8)$$

where  $H_{UP}$  represents the convolution operation. The input  $I_{LR}$  is the low-resolution image,  $I_{SR,S-1}$  is the output of the  $S-1$  reconstruction network.

Finally, the low-resolution image  $I_{LSR,S}$  obtained from upsampling is combined with the residual  $IR$  and  $S$  obtained from feature extraction to obtain the high-resolution image  $I_{SR,S}$  of  $s$ -level pyramid reconstruction.  $S$  can be obtained from equations (2) and (3) above. So far, the super-resolution image reconstruction of Laplacian pyramid structure is completed.

**3.3. CNB Building Module.** Figure 2 shows a Clique Block module with four layers. Except for input nodes  $F_{0,n,S}$  any two layers in the same Clique Block are bidirectional connected, that is, any layer is the input and output of another layer. Each Clique Block consists of two stages. The first stage is used to initialize all the layers in the Block. From the second stage, these layers will be extracted repeatedly.

Since this paper is designed specifically for image SR network. So, we are going to refine CilqueNet. First, we remove the batch standardized BN layer that consumes the same amount of GPU memory as the convolution layer, which increases the computational complexity and reduces the generalization performance of the network. Secondly, the existence of the pooling layer will cause the network to discard some pixel-level information, so we removed the pooling layer. Finally, we make full use of the layered features, which are neglected in CliqueNet networks, by using a local feature fusion (LFFNet) network to fuse all the features extracted in the second phase of the network  $k$  times. We refer to the improved structure as the CNB building block.

The 5-layer CNB building module designed in this paper is shown in Figure 3, including clique connected network and local feature fusion (LFFNet) network. In a clique connected network, except for input nodes, any two layers in the same CNB are bidirectional connected, and the layers are updated alternately. The first stage is used to initialize all the layers in the block. In the second stage, these layers will be extracted and updated repeatedly. Since more features are extracted in the second stage, in the local feature fusion network, we fuse the features extracted in the second stage for  $k$  times in the clique connected network as the input of the next CNB building module. CNB structure is shown in Figure 3.

**3.3.1. Clique Connected Network.** In the first stage, the input layer  $F_{0,n,S}$  initializes all other layers in the CNB building block through a one-way connection, and each updated layer is connected to update the next layer. We set the update layer as the top layer and other layers as the bottom layer, and connect the corresponding parameters of the bottom layer. To facilitate the subsequent derivation of the general formula, we rewrote the input node  $F_{n-1,S}$  as  $F_{0,n,S}$ . In the first stage, the input node in the NTH CNB in the pyramid S level is as follows:

$$F_{0,n,S}^1 = F_{n-1,S}. \quad (9)$$

Therefore, in the first stage, the  $c$ -layer output of the NTH CNB building module in the pyramid S hierarchy can be obtained by the general formula:

$$F_{c,n,S}^1 = \sigma \left( \sum_{l < c} W_{lc,n,S} * F_{l,n,S}^1 \right), \quad (10)$$

where  $\sigma$  represents the nonlinear activation function,  $*$  represents the convolution operation with parameter,  $W_{ij,n,S}$  represents the weight between layers in the newer process, and  $W_{ij,n,S}$  is reused in different stages, and each layer will receive feedback from the most recently updated layer.

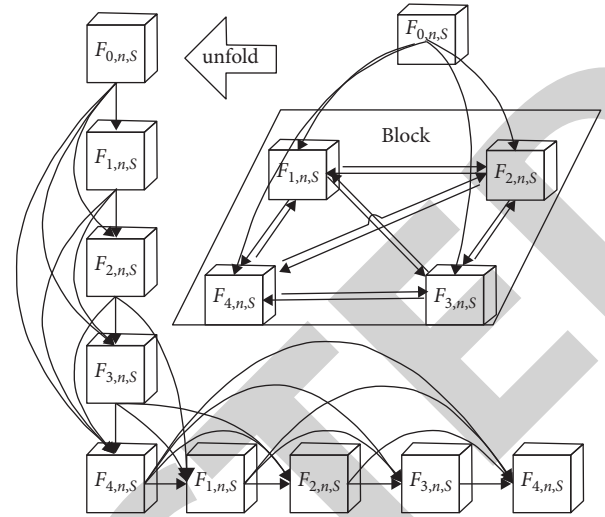


FIGURE 2: Clique Block structure.

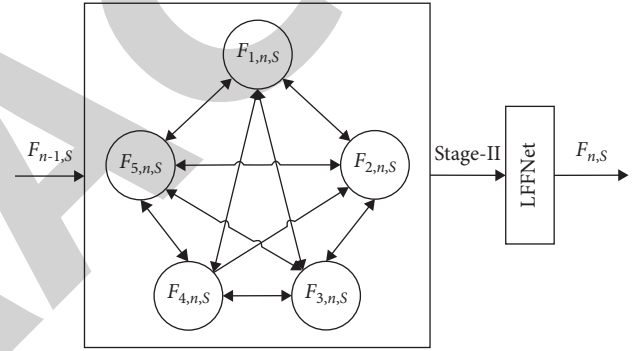


FIGURE 3: CNB structure.

Starting from the second phase, the layers are updated alternately. We also set the update layer as the top layer and the other layers as the bottom layer and connect the corresponding parameters of the bottom layer. Therefore, at the  $s$ -th level of the pyramid, when  $c$  ( $c \geq 1$ ) level, the  $k$ -th calculation is used. The output in the cycle can be obtained from the general formula:

$$F_{c,n,S}^k = \sum_{l < c} W_{lc,n,S} * F_{c,n,S}^1 + \sum_{m > c} W_{lc,n,S} * F_{c,n,S}^1. \quad (11)$$

A delivery with five CNBS is shown in Table 1. It consists of two phases; the first phase is used to initialize all the layers in the block, and the second phase begins; these layers will be extracted repeatedly for  $k$  alternate updates.

**3.3.2. Local Feature Fusion Network.** In the second stage, more features are extracted, so the local feature fusion (LFFNet) network is applied. Local features extracted by cycles. In this paper, the core size of the convolution layer is  $1 \times 1$  and the output information is adaptively controlled, so the output of the NTH CNB building module after fusion is  $F_{ns}$  which can be obtained by the following formula:



TABLE 1: Control table of policy parameters.

Tacit knowledge party	S knowledge innovation rate	0.05
	S knowledge aging rate	0.02
Knowledge receiver	R knowledge innovation rate	0.02
	R knowledge aging rate	0.02
	R knowledge integration and absorption capacity	(0,0.4)-(36,0.9)
	R network relationship ability level	Test parameters

$$F_{ns} = H_{LFF}^k [F_{c,n,S}^1, F_{c,n,S}^1, \dots, F_{c,n,S}^1], \quad (12)$$

where  $H_{LFF}^k()$  represents the convolution operation. So far, feature extraction of the CNB building module is completed.

#### 4. Simulation Experiment

According to the research objectives of this paper, the content of this section can be simulated from three aspects. First, adjust the level parameters of network relational capability to explore the influence on the effect of knowledge flow. The second is to adjust the absorptive capacity of knowledge integration and explore the influence on the effect of knowledge flow. Third, by changing the knowledge innovation rate of knowledge source and knowledge receiver, the law of knowledge flow in innovation market with different structures is explored.

**4.1. Simulation Result Analysis of Network Relationship Capability Level.** System policy parameters generally refer to constant and LOOKUP function. There are 6 policy parameters in this system, which are S knowledge innovation rate, S knowledge aging rate, R knowledge innovation rate, R knowledge aging rate, R knowledge integration and absorption capacity (denoted by LOOKUP function), and R network relationship ability level. In order to test the influence of the network relationship energy level of the knowledge receiver on the effect of knowledge flow, other policy parameters need to be controlled. Table 1 is the control table of other policy parameters, in which knowledge transfer situation is an auxiliary variable in the model, not an independent policy variable, so it is not specified in the table.

In this experiment, the knowledge innovation rate of S is 0.05, which is higher than that of R. S represents universities and R&D institutions in the collaborative innovation network, while R refers to core enterprises. Therefore, we can understand such an innovation market structure as the innovation market structure with universities and R&D institutions as the main innovation subjects. That is to say, for the core enterprises in our research, their innovative knowledge sources mainly come from universities and R&D institutions. Figure 4 is the simulation curve of the knowledge storage change of the corresponding knowledge receiver under the condition that other parameters remain unchanged and only the capability level parameter of the network relationship is changed.

Figure 5 is the simulation curve of the change of knowledge transferred by the corresponding knowledge receiver (enterprise) under the condition that other

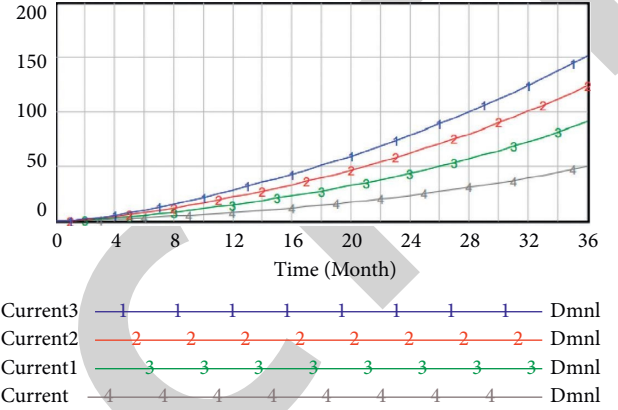


FIGURE 4: Simulation diagram of the relationship between network relationship capability and knowledge storage of the knowledge receiver.

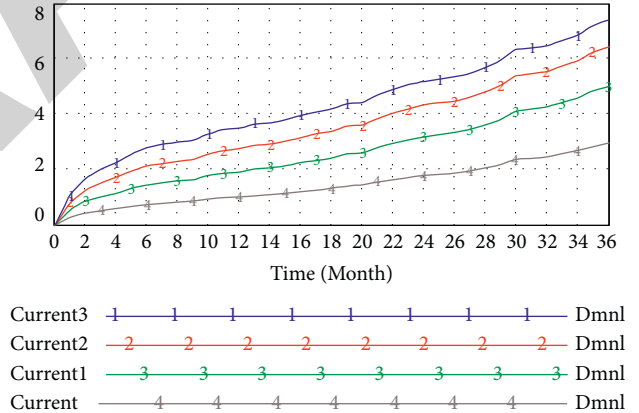


FIGURE 5: The simulation diagram of the relationship between network relationship capability and knowledge transfer quantity of the knowledge receiver.

parameters remain unchanged and only the network relationship capability level parameter is changed.

Diagram Current3/Current2/Current1/Current is represented by the curve, corresponding to the network relations ability level parameters for 0.8/0.6/0.4/0.2. It can be seen intuitively from the figure that, with the improvement of the network relationship capability level parameter, the r-transferred knowledge amount gradually increases in each period, and the increase of the transferred knowledge amount gradually decreases. For example, in the 18th month, the network relationship capability level parameter changes from 0.2 to 0.4, with an increase of 0.2 units. Knowledge transfer increased by about 0.7 units. When the network relationship capability level parameter changes

from 0.6 to 0.8, it also increases by 0.2 units, but the amount of transferred knowledge only increases by about 0.4 units, that is, the amount of transferred knowledge increases with the improvement of network relationship capability parameter, but it shows the characteristics of marginal decline. This reflects the ability level of the network relationship of the enterprise, which means the opportunity for the enterprise to exchange tacit knowledge with the outside world. This behavior makes the communication range wider, the enterprise knowledge search ability is stronger, and the enterprise is easier to find its own position in the market. However, when the network relationship capability of the enterprise reaches a certain level, with the increase of the number of weak relationships between the recipient enterprise and external knowledge sources, information redundancy will occur. In order to search for effective knowledge, the enterprise may have to pay a greater cost of information screening, which will reduce the efficiency of knowledge transfer of the enterprise. This also indicates that when the number of weak relationships between an enterprise and the outside world increases to a certain extent, it should pay more attention to the maintenance of strong relationships and the improvement of its own innovation ability.

## 5. Conclusions

In this paper, super-resolution image reconstruction algorithm, image denoising algorithm, and image warping correction algorithm of video preprocessing algorithm were studied and optimized based on deep learning. Later, though good results had been achieved, but also needed to continue to optimize the design, including the following: a Laplacian pyramid structure of the network super-resolution image reconstruction method. The experimental results verified that, in the subjective and objective effect, especially on the reconstruction of edge and line, the algorithm had good reconstruction. However, the network parameters and calculation amount increased, and the super-resolution amplification time was longer for maximum information flow and feedback mechanism and denser connections between layers, so further optimization is needed. Moreover, we also designed a fast image denoising algorithm based on OCT-Net, mainly on the Gaussian noise denoising processing; from the experimental results, the algorithm in different levels of Gaussian noise denoising obtained a good denoising effect and, at the same time, can effectively reduce the network computing resources. However, this algorithm is not effective in real noise removal, so it still needs further optimization. Furthermore, the DewarpNet image warping correction algorithm was optimized, designs the u-net ++ structure to optimize the shape network, and realizes the optimization of network parameters by pruning. However, the optimization algorithm cannot remove the regional shadows produced by the image warping well, so it still needs further optimization. Finally, the super-resolution image reconstruction algorithm was thoroughly studied and optimized and image denoising algorithm and image warping correction algorithm in the video preprocessing algorithm

were also optimized. After that, it can add the research and optimization implementation of the algorithms such as fog removal, rain removal, and dither removal.

## Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

## Conflicts of Interest

The author declares that he has no conflicts of interest.

## References

- [1] W. W. Powell, K. W. Koput, and D. L. Smith, "Interorganizational collaboration and the locus of innovation: networks of learning in biotechnology," *Administrative Science Quarterly*, vol. 41, pp. 116–145, 1996.
- [2] S. Interorganizational, "Relations in industrial systems: a network approach compared with the transaction cost approach," *International Studies of Management & Organization*, vol. 1, pp. 34–48, 1987.
- [3] J. L. Cummings and B. S. Teng, "Transferring R&D knowledge: the key factors affecting knowledge transfer success," *Journal of Engineering and Technology Management*, vol. 20, no. 12, pp. 39–68, 2003.
- [4] Y. Chen, H. Fan, and B. Xu, "Drop an octave: reducing spatial redundancy in convolutional neural networks with octave convolution," in *Proceedings of the International Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 3435–3444, IEEE, Long Beach, CA, USA, November 2019.
- [5] K. He, X. Zhang, and S. Ren, "Deep residual learning for image recognition," in *Proceedings of the International Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 770–778, IEEE, Las Vegas, CA, USA, November 2016.
- [6] U. Schmidt and S. Roth, "Shrinkage fields for effective image restoration," in *Proceedings of the International Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 2774–2781, IEEE, Columbus, OH, USA, September 2014.
- [7] S. Gu, L. Zhang, and W. Zuo, "Weighted nuclear norm minimization with application to image denoising," in *Proceedings of the International Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 2862–2869, IEEE, Columbus, OH, USA, September 2014.
- [8] O. Ronneberger, P. Fischer, and T. Brox, "U-net: convolutional networks for biomedical image segmentation," *Lecture Notes in Computer Science*, Springer, Munich, Germany, 2015.
- [9] G. Huang, Z. Liu, and L. Van Der Maaten, "Densely connected convolutional networks," in *Proceedings of the International Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 4700–4708, IEEE, Honolulu, HI, USA, July 2017.
- [10] A. Capaldo, "Network structure and innovation: the leveraging of a dual network as a distinctive relational capability," *Strategic Management Journal*, vol. 28, no. 6, pp. 585–608, 2007.
- [11] T. E. Smart, "Network positions and propensities to collaborate; an investigation of strategic alliance formation in a high-technology industry," *Administrative Science Quarterly*, vol. 43, no. 3, pp. 668–698, 1998.
- [12] A. K. Gupta and V. Govindarajan, "Knowledge flows within multinational corporations," *Strategic Management Journal*, vol. 21, no. 4, pp. 473–496, 2000.

- [13] B. McEvily and A. Zaheer, "Bridging ties: a source of firm heterogeneity in competitive capabilities," *Strategic Management Journal*, vol. 20, no. 12, pp. 1133–1156, 1999.
- [14] U. Zander and B. Kogut, "Knowledge and the speed of the transfer and imitation of organizational capabilities: an empirical test," *Organization Science*, vol. 6, no. 1, pp. 76–92, 1995.
- [15] M. A. Peteraf, "The cornerstones of competitive advantage: a resource-based view," *Strategic Management Journal*, vol. 14, no. 3, pp. 179–191, 1993.

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