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Applied Artificial Intelligence
An International Journal

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/uaai20

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To cite this article: Jin Wang (2023) Management Method Evaluation for Innovation and Entrepreneurship in College with Multi-Scale Feature Convolutional Network, Applied Artificial Intelligence, 37:1, 2224678, DOI: 10.1080/08839514.2023.2224678

To link to this article: https://doi.org/10.1080/08839514.2023.2224678

Published online: 15 Jun 2023.

APPLIED ARTIFICIAL INTELLIGENCE
2023, VOL. 37, NO. 1, e2224678 (2186 pages)
https://doi.org/10.1080/08839514.2023.2224678

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Management Method Evaluation for Innovation and Entrepreneurship in College with Multi-Scale Feature Convolutional Network

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ABSTRACT

Since the full implementation of the innovation-driven development strategy in the country, all regions and departments have placed great emphasis on the work of mass entrepreneurship and innovation, resulting in a significant increase in innovation and entrepreneurship. The national focus on mass entrepreneurship and innovation has shifted from quantitative to qualitative improvements, with greater attention being paid to improving substance rather than expanding scope. There is a growing trend among colleges to recognize innovation and entrepreneurial management as a significant achievement in college education and teaching. By prioritizing innovation and entrepreneurship management and professional education, the aim is to cultivate college students with an entrepreneurial spirit, and to develop inventive and entrepreneurial talent. Cultivating innovative talent is one way to apply the innovation-driven development plan and build a creative country. However, the implementation of the innovation and entrepreneurship development plan in the country has posed both new opportunities and challenges to the management of innovation and entrepreneurship education in colleges across the country. As a result, innovation and entrepreneurship have become increasingly important tasks that can help improve the management of innovation and entrepreneurship in these institutions. In order to address this issue, this paper proposes a neural network for evaluating innovation and entrepreneurship management methods in colleges, which combines convolutional neural networks with these tasks. Specifically, a multi-scale convolutional neural network is designed to more efficiently extract innovation and entrepreneurship management features in colleges, ultimately leading to improved model performance.

ARTICLE HISTORY
Received 13 April 2023
Revised 6 May 2023
Accepted 9 May 2023

Introduction

The prevailing economic development paradigm is increasingly anchored on information, knowledge, and technology as fundamental drivers of transformation. This development mode is continuously advancing the era of knowledge economy through innovation and entrepreneurship. The conventional

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investment model and industrial structure are unsustainable due to their proclivity for excessive investment, consumption, and extensive development, which run counter to the current society's low consumption, high added value, and intensive development goals. In line with the data technology era's general trend, development trends must continue to be promoted through innovation and scientific and technological progress. For innovation-driven development to thrive, there is a pressing need to enhance the innovation and entrepreneurship skills of the workforce. Unfortunately, there is a shortfall in creativity and entrepreneurship across society, as well as inadequacies in the training of new talent, to meet the demands of the data-driven economy and the shifting economic development model. Consequently, the state advocates for the vigorous promotion of mass entrepreneurship and innovation slogans to catalyze innovation and creativity among the populace and ride the wave of the era of innovation and entrepreneurship to achieve national and people's prosperity. As society and the economy grow exponentially, there is an increasing demand for inventive and entrepreneurial abilities in all sectors of life (Dong et al. 2019; Ghafoor et al. 2020; Mei and Symaco 2022; Nnakwe, Cooch, and Huang-Saad 2018; Yan et al. 2018).

Given the current societal challenge of a mismatch between the supply and demand for innovation, there is a pressing need to enhance innovation education. Educational institutions, such as colleges, have a crucial role in cultivating innovative abilities and entrepreneurial spirit, which are foundational to driving innovation-led development and building innovative societies. In addition to their responsibilities in educating future leaders, conducting scientific research, providing social services, and fostering cultural creativity, colleges must prioritize innovation and entrepreneurship education. This requires improving the training of innovators and entrepreneurs-in-training, as it is imperative for institutions of higher learning to nurture innovative skills as part of their core mission of disseminating knowledge and developing talent.

The integration of innovation and entrepreneurship education into college curricula is essential to address current societal issues and cultivate the skills required by the workforce. Therefore, colleges must collaborate to advance science and technology and contribute to societal progress. In order to better equip students for careers in creative fields, institutions must establish a framework for training entrepreneurially-minded students. Furthermore, improving the effectiveness and outcomes of innovation and entrepreneurship education necessitates the development of high-quality evaluation systems (Choi and Markham 2019; Lee and Yuan 2018; Lin et al. 2020; Liu et al. 2019; Zheng and Rui 2020).

The evident dearth of innovative and entrepreneurial skills has become a growing concern. A major issue faced by many recent college graduates is the lack of entrepreneurial spirit and capacity to initiate a business venture.

The root of this problem can be attributed to a lack of creativity and inadequate entrepreneurial education. Schools have recognized the importance of nurturing the next generation of business leaders and innovators, however, a comprehensive management and evaluation framework for entrepreneurial education and innovation remains absent. Despite the implementation of entrepreneurial education programs in large institutions, such programs are still in their infancy stage and their prevalence remains limited. Innovation and entrepreneurship courses are seldom integrated into the core curriculum of most educational institutions. Rather, they are offered as elective courses or lectures covering specific aspects of entrepreneurship. The absence of meaningful pedagogical instruction and inadequately informed educators has resulted in challenges in engaging students in innovation, while simultaneously fulfilling educational standards (Gaofeng 2021; Heaton, Siegel, and Teece 2019; Sang and Lin 2019; Xie et al. 2018; Yenchun Jim, Yuan, and Pan 2018).

The motivation behind the proposed paper is to address the challenges of managing innovation and entrepreneurship education in colleges in the context of the country's innovation-driven development plan. The paper aims to propose a neural network that can effectively evaluate innovation and entrepreneurship management methods in colleges, with the ultimate goal of improving innovation and entrepreneurship education and cultivating innovative talent.

The priorities of the paper include:

Addressing the challenges of managing innovation and entrepreneurship education in colleges: The paper recognizes that the implementation of the innovation-driven development plan in colleges poses new opportunities and challenges to managing innovation and entrepreneurship education. The proposed neural network aims to address these challenges by providing a more efficient and effective way to evaluate innovation and entrepreneurship management methods in colleges.

Improving innovation and entrepreneurship education: The paper emphasizes the importance of innovation and entrepreneurship education in cultivating inventive and entrepreneurial talent, and proposes a solution that can help improve the quality of such education.

Cultivating innovative talent: The paper recognizes that cultivating innovative talent is crucial to building a creative country and achieving the goals of the innovation-driven development plan. The proposed solution aims to contribute to this goal by enabling colleges to more effectively manage innovation and entrepreneurship education.

Overall, the paper is motivated by the need to address the challenges of managing innovation and entrepreneurship education in colleges and to improve the quality of such education, with the ultimate goal of cultivating innovative talent and achieving the country's innovation-driven development plan.

Related Work

Literature (McClure 2015) pointed out that the United States has taken innovation and entrepreneurship education as one of core links in entire learning stage from primary school to university, which is of great help to systematically develop the innovative thinking of college students. Literature (Hai-Bo, Zhang, and Ogbodo 2017) pointed out that entrepreneurship education is more to help understand their competitive advantages and find new ways to capture value. Teaching cases include not only start-up business management, but also how to deal with failure and change business strategies and actions. Literature (Ding 2017) pointed out in the research of college students that colleges need to serve social and economic development. Therefore, entrepreneurship education should be paid attention to in cultivating talents, and college students should be encouraged to play a more obvious role in social and economic development. Literature (Zhou 2016) mentioned that the innovative education atmosphere of Paksen Business School in the United States is very strong, and they have the entrepreneurial spirit of innovation, not afraid of taking risks, pursuing progress, and constantly surpassing themselves. And they also continue to conduct cooperative research with different disciplines, and this advanced awareness of education has brought new impetus to development for their school students. Literature (Jiang and Sun 2015) pointed out college students' education is necessary to improve students' independent creativity and encourage students to form innovative thinking habits. Literature (Zhou and Haixia 2012) believes that the education model should be the combination of theory and practice, enrich students' practical experience of entrepreneurship through various activities, and improve their innovation and entrepreneurship ability. In the view of the literature (Xiongwu 2016), the primary purpose of entrepreneurship education is to cultivate people's inventive consciousness as well as their entrepreneurial spirit and abilities. Literature (Gonghua 2017) believes that a university's entrepreneurial spirit entails a willingness to take risks. University's experience-oriented model places great emphasis on shaping and cultivating students' entrepreneurial skills, awareness, and spirit, and cultivating students' ability to realize entrepreneurship in a harsh social environment. Literature (Mars and Beth Ginter 2012) proposes that the success of entrepreneurship education in the UK can be sorted into three key points, namely, strong policy and financial support, standardized education management mechanism, and three-stage teaching methods, namely enlightenment education, general education, and professional education. Studies (Niccum et al. 2017) suggest that developing basic literacy is essential to entrepreneurial education, and that schools should implement more effective curricula, instructional strategies, and evaluation tools to achieve this goal. Literature (Yan and Hai Yan 2013) argues that the formation of entrepreneurial awareness and entrepreneurial spirit transcends the cultivation of employment-oriented traditional education.

Three typical models for innovation and entrepreneurial education are outlined in literature (Jing 2017). Innovative and entrepreneurial education can be taught in a variety of ways, and the three approaches are each unique and effective. There is a long-term project encompassing educational concepts, educational models, management systems and other areas of innovation and entrepreneurial education management that requires coordination between the government and universities as well as other sectors of society (Adhikari et al. 2014). According to research (Dahlstrand and Stevenson 2010), innovation education emphasizes the mind whereas entrepreneurship education emphasizes the hands. The two strategies work together to cultivate students' entrepreneurial and innovative mind-sets, and they are both essential. Entrepreneurship and innovation education in higher education is defined in literature (Weilerstein and Byers 2016) as colleges' ability to organize and manage their resources in such a way that they can impart their entrepreneurial know-how to students while also nurturing their entrepreneurial aspirations, employment opportunities, as well as entrepreneurial needs. Colleges, according to the literature (Shi and Yonezawa 2012), should integrate the current operation of the higher education teaching system into the implementation process of mass entrepreneurship and innovation as the primary body.

Method

This work combines innovation and entrepreneurship management in colleges with neural networks (MSCNN). First, this work designs a multi-scale convolutional neural network for more efficient feature extraction of innovation and entrepreneurship management features to improve model performance. Secondly, this work improves and optimizes the model from three aspects: network structure, activation function, and weight initialization method. Finally, sufficient experiments verify validity for model, which can effectively evaluate innovation and entrepreneurship management. This work expands feature of innovation and entrepreneurship management into a two-dimensional form, and then uses convolutional networks for method evaluation, similar to the two-dimensional image classification task.

CNN Knowledge

Convolutional neural network extracts feature information through the connection of multi-layer network structures, and is mainly used in CV and NLP. CNN imitates the cognitive mode of the biological visual cortex, and proposes concept of local receptive field, uses convolution kernel to extract the local information in the data layer by layer, and finally performs recognition and analysis processing.

The convolutional layer is the main structure for extracting data features in the convolutional neural network, and its interior is composed of many convolution kernels. In image processing, in order to extract image edges or smooth images, convolution is often used for filtering. The convolution kernel is a template for feature representation. The larger the calculated value, the more similar the feature representing the current position of the image is to the designed template feature. In the feature extraction process of the convolution layer, in addition to the above-mentioned convolution operation, in order to selectively highlight the role of some pixels, a bias parameter is added after each convolution operation.The output layer size is:

$$W_{out} = \frac{W - F + 2P}{S} + 1 \tag{1}$$

$$H_{out} = \frac{H - F + 2P}{S} + 1 \tag{2}$$

The convolutional neural network's pooling layer is one of the three layers. The convolutional layer's output is fed into this filter, which performs feature screening on it. More feature templates can't be set for feature extraction in the convolutional layer because of parameter limitations. It is possible to reduce the amount of data needed to compute and the size of the feature map by pooling. At the same time, when the space size is reduced, the number of feature templates can be expanded, and more abundant feature information can be extracted. However, the operation of pooling also loses the information on the spatial scale of the feature image. The prevailing view that the role of pooling layers is effective can be seen in most advanced network models today. Pooling operations are generally divided into two types, one is average pooling, in which the average value of each area is used as the network output. The other is max pooling, which outputs the maximum value in each region as the main feature.

$$x_j^k = f\left(\beta \times down\left(x_i^{k-1}\right) + b_j^k\right) \tag{3}$$

The fully connected layer is often used in classification and recognition tasks. It compresses three-dimensional feature information of the previous layer to form a one-dimensional vector. Similar to the traditional neural network, the fully-connected layer adopts a way of directly connecting the elements of the upper and lower layers, that is, each neuron needs to establish a connection with all the elements of the previous layer. Therefore, the number of parameters involved in the fully connected layer is huge.

$$x_j^k = f\left(\sum_i x_i^{k-1} * w_{ij}^{k-1} + b_i^k\right) \tag{4}$$

The activation function is an important part of the convolutional neural network. If there is no activation, network model will become a linear fitting model. In the feature fitting task, for simple problems, feature fitting can be performed by a linear function. For some complex problems, the error brought by linear fitting is very large, and even does not achieve the expected effect. In feature extraction, convolutional layer adopts the method of linear feature extraction. For each unit, feature extraction is performed by linear weighted superposition. In this way, no matter how many layers the network is designed, the final expression of the model is still a linear function. In real environment, the data is generally linearly inseparable, and only by means of linear stacking in convolutional layer, CNN cannot maximize the distribution of the fitted data. To solve this issue, the researchers proposed an activation function to enhance expressive ability. Typical activation functions are:

$$Sigmoid(x) = 1/(1 + \exp(-x)) \tag{5}$$

$$Tanh(x) = (\exp(x) - \exp(-x))/(\exp(x) + \exp(-x)) \tag{6}$$

$$ReLU(x) = \max(0, x) \tag{7}$$

Batch regularization is a deep neural network training technique proposed by Google in 2015. Its role is to accelerate the convergence rate of the model during model training, and more importantly, it alleviates the gradient vanishing problem of deep networks to a certain extent. Most of the current popular convolutional neural networks use deep structures to obtain better model fitting effects, so batch regularization has become a standard skill in convolutional neural networks. Batch regularization is to regularize each batch of data. The network training process is accompanied by the update of parameters. Except for the input layer, each layer accepts input data distribution of previous layer, which is always changing, because the parameter update causes the input data distribution of the subsequent layer to change. The purpose of batch regularization is to solve issue of changes in distribution of intermediate data layers during network model training.

Multi-Scale CNN

In the process of feature extraction, single-scale feature extraction will result in low network performance. The use of multi-scale feature networks can effectively extract more comprehensive information. In this section, a multi-scale convolutional network is designed to perform more efficient feature extraction on innovation and entrepreneurship management methods.

Inception structure is core of the multi-scale network. It has four branches for the input, and convolution or pooling operations are performed on the input using convolution kernels of different sizes. Then the results are concatenated and output in the feature dimension. The most primitive Inception structure is shown in Figure 1.

The information contained in the stacking and concatenation of these features is much richer than using a single convolutional layer. However, in this original Inception structure, all convolutional layers directly convolve the output of the previous layer. Not only is this too computationally expensive, but the concatenation of the 4 results directly increases the thickness of the feature map by a factor of 4. In order to solve this issue, a convolutional layer is utilized before convolutional layer and after maximum pooling layer. These convolutional layers can reduce dimension, thereby reducing the thickness of the feature maps after concatenation. This forms the current Inception structure, shown in Figure 2.

This structure firstly uses a 1×1 convolutional layer to reduce dimension, secondly, extracts and concatenates the feature maps simultaneously on multiple scales. Using a 1×1 convolution kernel in the network can not only reduce the feature dimension and parameters, but also fuse the feature information across channels to a certain extent, enriching the extracted feature

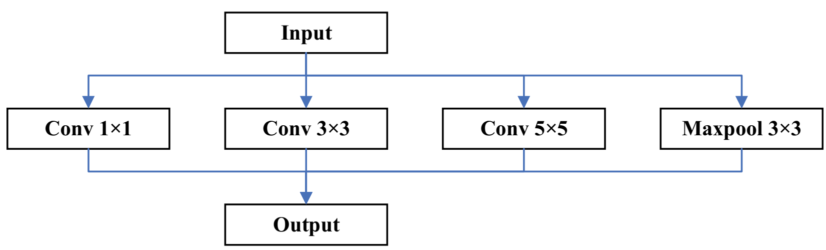

Figure 1. The structure of inception.

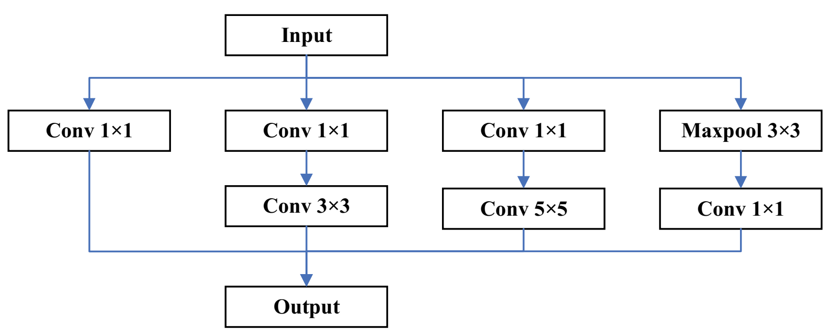

Figure 2. Improved inception.

information. In addition, the addition of 1×1 convolutional layers can deepen network layers and improve nonlinearity while keeping the feature map size unchanged.

The traditional convolution layer only uses a convolution kernel of one scale to convolve the input, and the extracted features will be evenly distributed on the feature map according to this scale, and the feature map can be regarded as a sparsely distributed feature set. While Inception convolves and aggregates the input at multiple scales at the same time, the extracted features are no longer uniformly distributed. Instead, highly correlated features are clustered together, and this feature map can be viewed as a combination of multiple densely distributed sub-feature sets. After the input feature map undergoes multiple such multi-scale feature extraction and aggregation, its redundant information becomes less and less, and the feature information becomes more and more refined. This high-quality feature set can naturally accelerate the convergence speed of the model during backpropagation training. MSCNN based on the Inception structure is shown in Figure 3.

The network includes a series of convolutional layers, activation layers, pooling layers, Inception, BN layers and FC layers. Each layer has different functions and parameter settings to accomplish different tasks.

Improvement on MSCNN

At the end of the traditional CNN model, several fully connected layers are usually used to integrate and classify the extracted features. However, the dense connection characteristics of the fully connected layer make it contain a huge number of parameters, which is prone to overfitting. Although some methods have been developed to alleviate the over-fitting phenomenon of FC layer, the problem of too many parameters has not been well solved. The GAP is used to replace FC. This method has also been adopted by many subsequent CNN models. The multi-scale CNN designed in this section uses GAP to classify the feature information extracted by the front layer, and adds dropout operations to suppress overfitting. Figure 4 shows the overall structure of the network model.

MSM is the improved multi-scale module, the pipeline is illustrated in Figure 5. The parameters of the convolutional layers on each branch are adjusted, and the 5×5 convolution is replaced by two superimposed 3×3

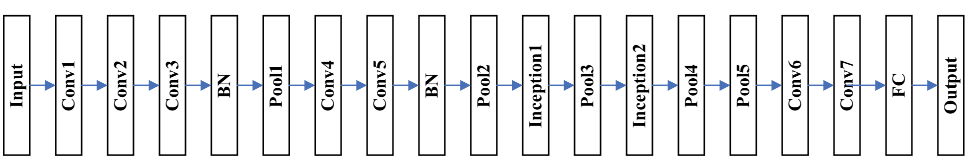

Figure 3. The pipeline of MSCNN.

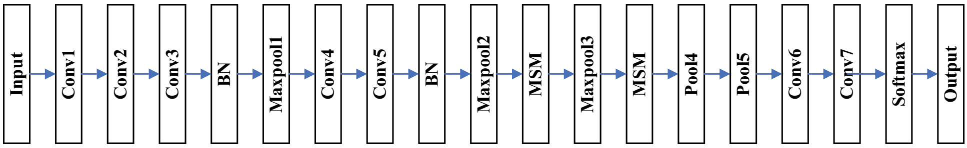

Figure 4. Improved MSCNN.

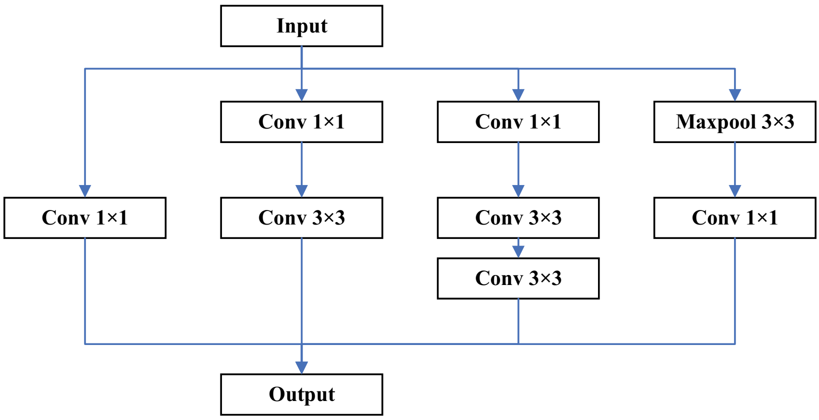

Figure 5. The structure of MSM.

convolutions, which can reduce the amount of computation by about 30% with the same effect.

To improve the nonlinear expression capability of the entire network model, activation functions are commonly utilized in deep neural networks to nonlinearly alter the hidden layer's output. By multiplying negative values by a tiny coefficient, the redesigned LReLU function prevents zero gradients from occurring. Therefore, here we try to replace the activation function in MSCNN from ReLU to LReLU.

$$LReLU(x) = \begin{cases} x, x > 0 \\ ax, others \end{cases} \tag{8}$$

Before the training process starts, the weight parameter initialization operation is performed on each convolutional layer and the fully connected layer, that is, the parameters are randomly assigned. Then the neural network starts to perform activation forward propagation and gradient back propagation according to these parameters, so as to continuously update the parameters to make the network optimal. For shallow networks, the transfer process of activation values and gradients is short, and the update range of weights is also relatively narrow. However, for a deep neural network, if initial weight is set large or small, gradient explosion or gradient disappearance will easily occur in the process of layer-by-layer transmission, making it difficult for the model to converge. General initialization methods include constant initialization and random initialization. Obviously, constant initialization does not work in neural network. To avoid problem of gradient explosion or gradient disappearance, random initialization should control the size of the generated weight within a range, that is, limit the variance of the weight to make it obey Gaussian distribution or uniform distribution. However, as network layers deepens, output value of activation function will gradually approach zero. The researchers propose a weight initialization method for ReLU, called He initialization. The He initialization considers the influence of the ReLU function on the distribution of activation values. Based on the Xavier initialization, it is proposed to keep the variance between the state value and the gradient of the activation value in each layer unchanged. This work uses this optimization method to assign the initial value of the network to improve the model performance.

Experiment and Discussion

Dataset and Experimental Detail

The data set used in this work is collected from the innovation and entrepreneurship management data of domestic colleges. It contains a total of 30,481 samples, of which 18,924 are training samples and the remaining 11,557 are test samples. The innovation and entrepreneurship management characteristics of each sample are 10 dimensions, as shown in Table 1, and the corresponding label is the quality level of innovation and entrepreneurship management methods. The feature is expanded to 200×200 format. The urban experimental environment of this experiment is shown in Table 2.

Evaluation on Training

In the deep learning method, network training is an indispensable link and a guarantee of network performance. This work exhibits the loss change and performance change during the training process to examine the

Table 1. The feature of innovation and entrepreneurship management.

Feature	Meaning
x_1	School-enterprise cooperation
x_2	Governmental support
x_3	College investment
x_4	Mechanism guarantee
x_5	Entrepreneurial atmosphere
x_6	Hardware facilities
x_7	Curriculum structure
x_8	Teacher construction
x_9	Student evaluation
x_{10}	Innovative achievement

Table 2. The experimental environment.

Name	Parameter
Operating system	Ubuntu 18.04
CPU	Intel Core i7
Memory	32GB
Deep learning framework	Pytorch 1.6

network's training process. Figures 6 and 7 show the results of the experiments.

The training loss lowers and the training accuracy rises as the network iterates, as is obvious. The network has obtained convergence when the training reaches 60 epoch, as should be mentioned. The loss is no longer significantly decreased, and the accuracy is no longer significantly increased.

Method Comparison

To verify the effectiveness for MSCNN, it is compared with other methods. The compared methods include traditional metric learning such as SVM and BP, also including deep learning method such as DNN and CNN, and the experimental results are demonstrated in Table 3.

Compared with other methods, MSCNN can achieve the best evaluation performance: 96.7% accuracy and 94.5% recall. Compared with the best listed

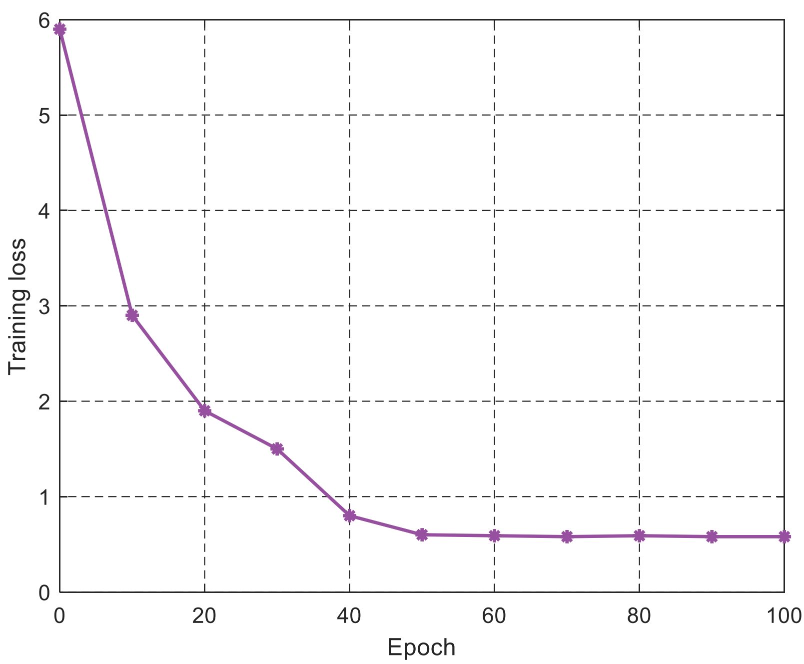

Figure 6. The training loss.

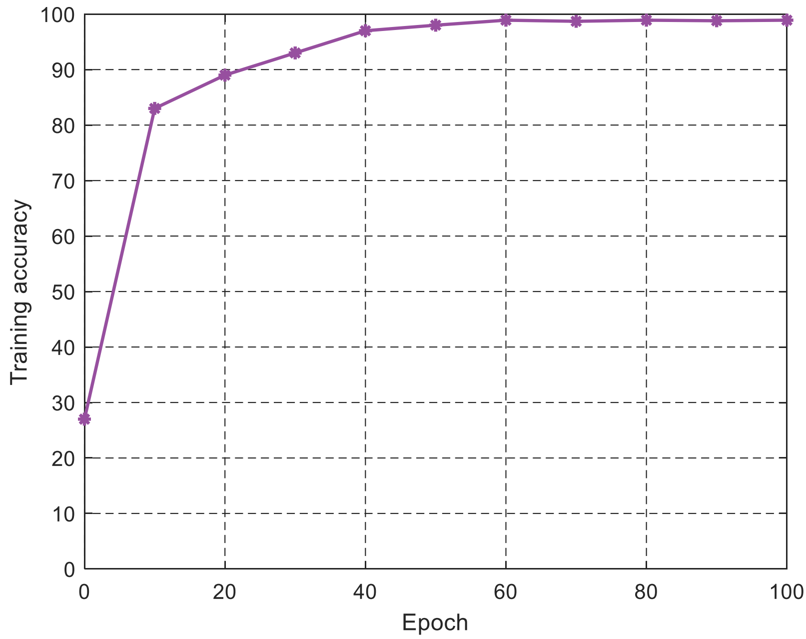

Figure 7. The training accuracy.

Table 3. Comparison of MSCNN with others.

Method	Acc	Rec
SVM	85.5	82.9
BP	87.3	85.9
DNN	91.6	89.5
CNN	94.1	92.1
MSCNN	96.7	94.5

method CNN, it can obtain 2.5% accuracy improvement and 2.4% recall improvement.

Evaluation on Multi-Scale Feature

For innovation and entrepreneurship management strategies, MSCNN uses multi-scale properties. The multi-scale method is contrasted to the single-scale feature method in order to demonstrate its usefulness. Figure 8 shows the results of the experiments.

Evaluation on LReLu

This work uses the LReLU activation function to optimize the network. To verify the effectiveness of this strategy, the evaluation performance when using LReLU is compared with the evaluation performance when

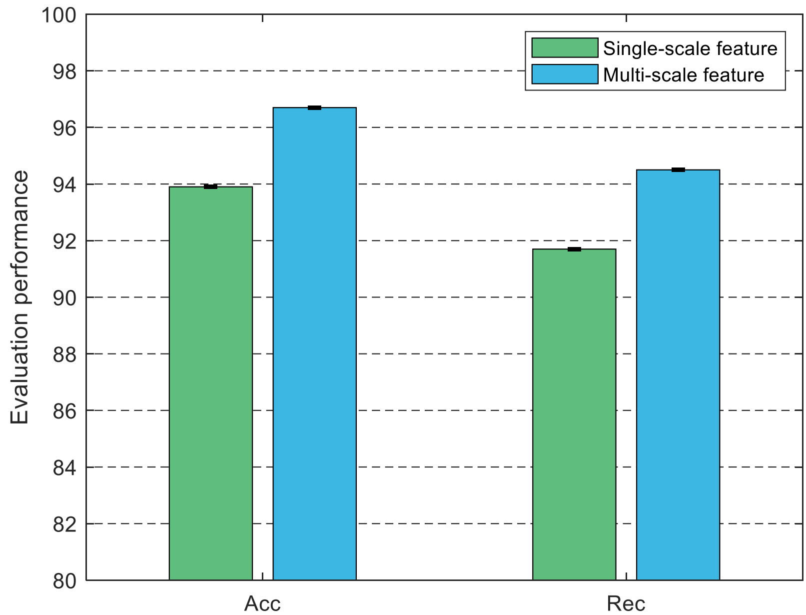

Figure 8. Evaluation on multi-scale feature.

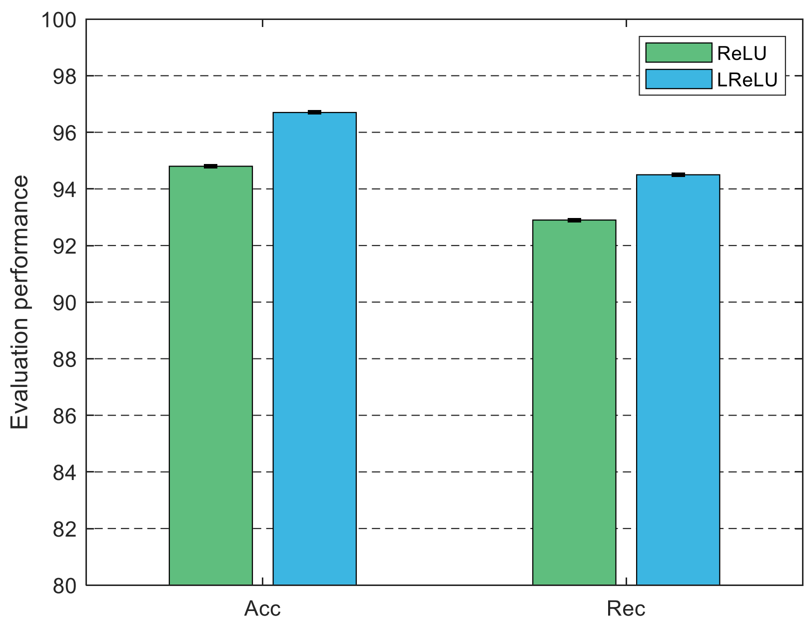

Figure 9. Evaluation on LReLU.

using traditional ReLU. The experimental results are demonstrated in Figure 9.

It can be seen MSCNN using LReLU can achieve the highest accuracy and precision. Compared with ReLU, 1.9% accuracy improvement and 1.6% recall improvement can be obtained, which proves the effectiveness and correctness of using LReLU in this paper.

Evaluation on HE Weight Initialization

This work uses the HE method to initialize network weight. To verify the effectiveness of this strategy, the evaluation performance when using HE is compared with the evaluation performance when using traditional Gaussian initialization. The experimental results are demonstrated in Figure 10.

It can be seen MSCNN using HE weight initialization can achieve the highest accuracy and precision. Compared with Gaussian initialization, 1.4% accuracy improvement and 1.2% recall improvement can be obtained, which proves the effectiveness and correctness of using HE weight initialization in this paper.

Evaluation on Improved Inception

This work uses the improved Inception to promote network. To verify the effectiveness of this strategy, the evaluation performance when using improved Inception is compared with the evaluation performance when using traditional Inception. The experimental results are demonstrated in Table 4.

It can be seen MSCNN using improved Inception can achieve the highest accuracy and precision. Compared with Inception, 1.1% accuracy

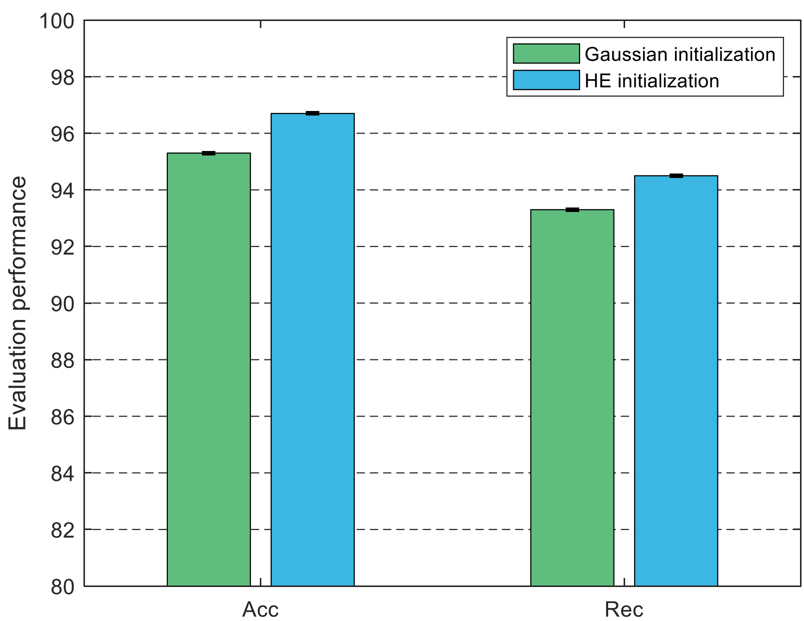

Figure 10. Evaluation on HE weight initialization.

Table 4. Evaluation on improved inception.

Method	Acc	Rec
Inception	95.6	93.6
Improved Inception	96.7	94.5

improvement and 0.9% recall improvement can be obtained, which proves the effectiveness and correctness of using improved Inception in this paper.

Discussion

The proposed paper uses a neural network approach, specifically a multi-scale convolutional neural network, to evaluate innovation and entrepreneurship management methods in colleges. Compared to deep and ensemble learning, the proposed approach has some improvements and differences.

Firstly, the proposed approach is more specific to the task at hand, which is to evaluate innovation and entrepreneurship management methods in colleges. Deep and ensemble learning approaches are general-purpose machine learning methods that can be applied to a wide range of tasks. The proposed approach, on the other hand, is specifically designed to extract relevant features from the data related to innovation and entrepreneurship management in colleges.

Secondly, the proposed approach uses a multi-scale convolutional neural network, which is specifically designed to extract features at multiple scales. This is important for the task of evaluating innovation and entrepreneurship management methods in colleges because these methods can vary widely in their scope and complexity. By extracting features at multiple scales, the proposed approach can better capture the relevant information in the data and make more accurate evaluations.

Finally, the proposed approach is more efficient than some ensemble learning approaches, which can require training and combining multiple models. The proposed approach is a single model that can extract features at multiple scales, reducing the need for training and combining multiple models.

In summary, the proposed paper improves upon deep and ensemble learning approaches by using a more specific, task-oriented approach and a multi-scale convolutional neural network to more accurately capture the relevant information in the data related to innovation and entrepreneurship management in colleges.

There are several factors or variables that may affect the experiment environment of the proposed neural network for evaluating innovation and entrepreneurship management methods in colleges. Some of these factors include:

Data quality and quantity: The success of the proposed neural network will depend on the quality and quantity of data available for training. The data used must be representative of innovation and entrepreneurship management methods in colleges across the country, covering a diverse range of institutions and regions.

Model hyperparameters: The performance of the neural network will also depend on the values chosen for its hyperparameters, such as learning rate, batch size, and regularization. The optimal values for these hyperparameters may vary depending on the specific task and data used.

Hardware and software environment: The performance of the neural network will also be affected by the hardware and software environment used to train and evaluate the model. For example, the type and speed of the CPU and GPU used, the memory available, and the software used for training and evaluation can all affect the performance of the model.

Bias in data or model: Bias in the data used to train the neural network or in the model itself can also affect the results. For example, if the data used to train the model is biased toward certain types of institutions or regions, the model may not perform well on data from other types of institutions or regions.

Generalization of the model: The neural network may perform well on the data used for training and evaluation, but its performance on new, unseen data may be different. It is important to ensure that the model can generalize well to new data and that its performance is consistent across different datasets.

It is important to carefully consider and control these factors when designing and conducting experiments with the proposed neural network for evaluating innovation and entrepreneurship management methods in colleges, in order to ensure that the results are reliable and valid.

Some general methods that could be used to address these variables:

Data quality and quantity: The author may collect data from a diverse range of colleges and regions to ensure that the data is representative of innovation and entrepreneurship management methods in colleges across the country. Additionally, the author may perform data preprocessing steps, such as removing duplicates and outliers, to improve the quality of the data.

Model hyperparameters: The author may use a grid search or random search to explore different values for the hyperparameters and choose the optimal values based on the performance of the model on a validation set. Additionally, the author may use techniques such as early stopping or cross-validation to prevent overfitting and ensure that the model generalizes well.

Hardware and software environment: The author may use hardware and software environments that are commonly used for deep learning, such as a GPU-accelerated workstation or cloud-based computing resources. Additionally, the author may use popular deep learning frameworks, such as TensorFlow or PyTorch, to ensure compatibility with existing libraries and tools.

Bias in data or model: The author may perform exploratory data analysis to identify any biases in the data and take steps to mitigate them, such as oversampling or undersampling certain classes or regions. Additionally, the author may use techniques such as dropout or data augmentation to reduce the risk of overfitting and improve generalization.

Generalization of the model: The author may evaluate the performance of the model on a test set that is separate from the training and validation sets to ensure that the model generalizes well to new, unseen data. Additionally, the author may use techniques such as transfer learning or fine-tuning to adapt the model to new datasets or tasks.

These are just a few general methods that could be used to address the variables mentioned in my previous response. The specific methods used by the author would depend on the details of the experiment and the available resources.

Conclusion

Management of innovation as well as entrepreneurial education is an educational concept that is geared to the needs of national economic development and national strategy. Promoting innovation and entrepreneurship is critical for the long-term development, as well as for advancement of educational reforms and the upkeep of a well-trained students. Colleges have been given new tasks in the new period, including improving management of innovation and entrepreneurship. Our country's institutions have only recently begun teaching students about innovation and entrepreneurship, the management model is still being explored and researched. There are many challenges in the management of innovation and entrepreneurship, including how to integrate innovation and entrepreneurship with traditional education and how to improve the teaching staff and curriculum. As a foundation for improving colleges' entrepreneurship and innovation management, evaluation and research on management quality of innovation as well as entrepreneurship management at colleges is essential. An essential task in this context is how to effectively analyze the management methods of innovation and entrepreneurship to enhance the management. Using this task and a neural network, this paper presents an algorithm for evaluating collegiate innovation and entrepreneurship management strategies. It begins by developing a multi-scale convolutional neural network that can extract aspects of innovation and entrepreneurship in universities more efficiently.

The novelty of the proposed approach lies in the use of a multi-scale convolutional neural network to evaluate innovation and entrepreneurship management methods in colleges. While convolutional neural networks (CNNs) have been widely used for image recognition tasks, the proposed approach extends the use of CNNs to the domain of innovation and entrepreneurship management in colleges. The use of a multi-scale CNN allows for more efficient feature extraction across multiple scales of the input data, which can be particularly useful for analyzing complex and heterogeneous data such as that found in innovation and entrepreneurship management.

In addition, the proposed approach is novel in its focus on evaluating innovation and entrepreneurship management methods in colleges, which is an important and growing area of interest in many countries. By providing a neural network-based approach to evaluating these methods, the proposed approach has the potential to contribute to the development of more effective and efficient methods for innovation and entrepreneurship management in colleges.

Overall, the proposed approach represents a novel application of deep learning techniques to the domain of innovation and entrepreneurship management in colleges, with potential applications in both research and practice.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

The research is supported by the General Humanities and Social Sciences Research Project of Henan Provincial Department of Education, for the study on the path of action for vocational education to prevent the risk of poverty in the post-poverty era (No. 2023-ZZJH-153).

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