Scholar Publishing Group
International Journal of Neural Network
https://doi.org/10.38007/NN.2020.010401
ISSN 2790-2692 Vol. 1, Issue 4: 1-9

Optimal Analysis of Weather Forecast Supporting Convolutional Neural Networks

Nan Yang*
Shandong Police College, Jinan, China
**corresponding author*

Keywords: Convolutional Neural Network, Weather Forecast, CNN, Optimization Analysis

Abstract: In recent years, with the acceleration of social informatization, people's requirements for weather forecasting have gradually increased. Severe convective weather has attracted the attention of the meteorological department because of its characteristics of strong suddenness and great destructive power. As a forecasting method to prevent severe convective weather, short-term forecasting has important research significance. The purpose of this paper is to study the optimization analysis of meteorological forecasts supported by convolutional neural networks. In this paper, the deep learning method is used to conduct an applied research on the precipitation of short-term and imminent forecasting. Precipitation short-term forecasting is essentially the prediction of future radar echoes from a series of radar echo sequences, which can be regarded as a spatiotemporal sequence prediction problem. Based on the research and summary of commonly used neural networks, this paper refers to ConvLSTM (ConvolutionalLSTM) Structure A ConvGRU model (ConvolutionalGRU) combining Convolution Neural Network (CNN) and GRU (Gated Recurrent Unit) is proposed. Since the structure of GRU is simpler than that of LSTM, the effect is not much different. This model is compared to The ConvLSTM structure has faster training speed and smaller memory requirements. Another work of this paper is to improve the convolutional layer based on VGGNet (VisualGeometryGroupNet), using multiple small convolution kernels to stack instead of large convolution kernels, reducing the number of parameters and improving the feature extraction ability of the network. This model gives full play to the advantages of convolutional neural network and GRU, that is, the spatial feature extraction ability of convolutional structure and the memory ability of GRU to deal with time series problems. Finally, the prediction effects of the model and the optical flow method are compared through experiments to verify the applicability of the model in the short-term precipitation forecasting problem.

1. Introduction

In recent years, with the acceleration of the informatization process of the meteorological industry, more and more new technologies have been applied in the field of forecasting. In the field of meteorological forecasting, short-term forecasting has always been an important subject. The goal of this task is to accurately and real-time forecast meteorological conditions in a local area over a short period of time (eg, 0-6 hours). Compared with various long-term, medium-term and short-term forecasts, short-term forecasting is a forecast model that appears later. Compared with short-term forecasting, short-term forecasting has a shorter forecast validity period. The forecast validity period of short-term forecasting is mainly concentrated in 0. From 12 hours to 12 hours, it is mainly for the prediction of small and medium-scale weather systems, especially in the forecast of strong convective weather systems, short-term forecasting is very important [1-2]. However, this paper mainly focuses on short-term forecasting in the field of precipitation. With the rapid development of computing power and the rapid expansion of data, modern human beings have begun to enter the era of big data, and efficient use of data has become an important direction for the industry's leading development. Deep learning is flourishing under this background and is evolving into the grand innovation revolution. Deep learning has also become the hottest field of artificial intelligence. Among them, the most widely used convolutional neural network in the field of image processing and LSTM, which is good at dealing with spatiotemporal sequence problems, are branches that develop very rapidly [3-4].

In the research on the optimization analysis of meteorological forecast supporting convolutional neural network, many scholars have studied it and achieved good results. For example, Moon YJ and others used principal component analysis to process precipitation data, and used neural network The daily precipitation in the basin is estimated and calculated [5]. Landa V et al. used BP neural network and optimal subset regression coupling to establish a model for long-term forecast of runoff in the Danjiangkou watershed during the period of time, and the forecast effect was stable and effective [6].

This paper introduces the research background of short-term precipitation forecasting, summarizes the difficulties, and introduces the development of short-term precipitation forecasting at home and abroad as well as the application of neural network in short-term precipitation forecasting at home and abroad. And describe the work done and the structure of the article. The related deep learning technology is introduced, and its development history is briefly described. Among them, the convolutional neural network and the long short-term memory network LSTM are mainly introduced, and the connection between the neural network and the short-term precipitation forecast and the feasibility of combined application are discussed. This paper introduces the improvement of ConvLSTM applied to short-term precipitation forecasting, including replacing LSTM structure with GRU structure, applying the design idea of VGGNet network, replacing large convolutional layers with stacking of small convolutional layers, and introducing the method applied to precipitation forecasting. The preprocessing method of radar echo data is presented, and the realization scheme of the precipitation short-term and imminent forecasting system is expounded. Describe the steps of the data set, parameter setting, etc., briefly describe the experimental process, evaluate the experimental results according to different evaluation standards, and compare and analyze different prediction methods. Finally, the application prospects and technical contributions of the technical realization of this paper are summarized and prospected.

2. Research on Optimal Analysis of Weather Forecast Supporting Convolutional Neural Networks

2.1. Forward Propagation of Convolutional Neural Networks

The forward propagation of the convolutional neural network is divided into two steps. The first step is the convolution operation, and then the second step is to perform a subsampling operation on the features obtained by the convolution operation. They are handled by convolutional layers and pooling layers, respectively. The process of forward propagation is as follows: the input of the sample can be a two-dimensional black and white picture, then the input layer X is a matrix, the value of each position of the matrix is determined by the pixels of the picture, then the convolution kernel W is also a matrix, if the sample is For color pictures, the input layer X can be a high-dimensional tensor. Correspondingly, X is a high-dimensional tensor. The input layer is forwarded to the convolution layer, and the convolution layer performs the convolution operation on the input image set to get A series of feature maps can be expressed by the following formula [7-8]:

$$X_j^l = f\left(\sum_{i\in M_j}\left(X_i^{l-1} * K_{ij}^l + b_j^l\right)\right) \tag{1}$$

The superscript represents the number of layers, Xj represents the jth feature map of the lth layer, f () represents the activation function, Mj represents the input data set, * represents the convolution, K represents the ith feature map of the l-1th layer and The convolution kernel connected to the jth feature map of the lth layer, and bj is the bias term. In order to better identify the edge, when convolution, you can add several circles of 0 around the input matrix and then perform convolution. This behavior becomes padding [9-10] .

The pooling layer sub-samples the feature map obtained after convolution, a commonly used sub-sampling method.

There are maximum subsampling, mean subsampling, etc. Through subsampling, not only the useful information of the image is retained, but also the input image is reduced and summarized. The operation of the pooling layer can be expressed by the following formula:

$$X_j^l = f\left(down\left(X_j^{l-1} + b_j^l\right)\right) \tag{2}$$

Where Xk represents the jth feature map of the lth layer, f () represents the nonlinear activation function, and the down function is a subsampling function, which means that the bias term is passed to the fully connected layer through the input data of several convolutional layers and pooling layers. , the operation here is the same as the traditional neural network[11- 12] .

2.2. Meteorological Prediction Method Based on Neural Network

Neural networks have been widely used in various application fields and problems since the 1990s due to their unique characteristics of solving nonlinear problems. The meteorological forecasting problem is a typical nonlinear problem, and neural network has also been the most in-depth application in the field of meteorological forecasting. In 1987, Neural Ware Company of the United States began to apply neural networks in the field of atmospheric science, and proposed an artificial neural network weather forecasting system. The model uses the air pressure, temperature and wind direction and speed observed on the ground as samples, and through the training of the network model, predicts the future sunny and rainy conditions. The model also checks and corrects the forecast model through the detection of actual data. The conclusion shows that the model has a certain improvement in accuracy compared with other forecasting methods at that time [13-14] .

In the experiment, the temperature, wind speed and related humidity data are used as training and prediction variables, and the statistical results are used to evaluate the effect of each model. The experimental results show that most models can achieve reasonable prediction accuracy. The authors argue that using a larger training set, different training algorithms, and more atmospheric data improves accuracy.

Most artificial neural networks require data normalization of input variables and target variables in advance, which means that the original data is transformed into the range of [−1, 1] or [0, 1]. K.Abhishek et al. developed a neural network model that can directly use raw data, and examined the applicability of artificial neural network methods. By predicting the daily maximum temperature for one consecutive year, the performance of neural networks with different activation functions, number of hidden layers and number of neurons is evaluated and compared. Paras et al. pointed out that the selection of statistical indicators such as moving average, skewness and kurtosis coefficient can extract hidden trends in meteorological changes, which can be used as model features. And pointed out that the weather forecast based on the neural network method can produce good results, which can be considered as an alternative to the traditional meteorological method [15-16] .

2.3. Functional Requirements of Meteorological Data Analysis System

The meteorological data analysis system can be divided into 3 major types and 6 major modules in terms of requirements, and each module has its own sub-category, and each sub-category contains different elements. The overall structure of the system is shown in Figure 1 :

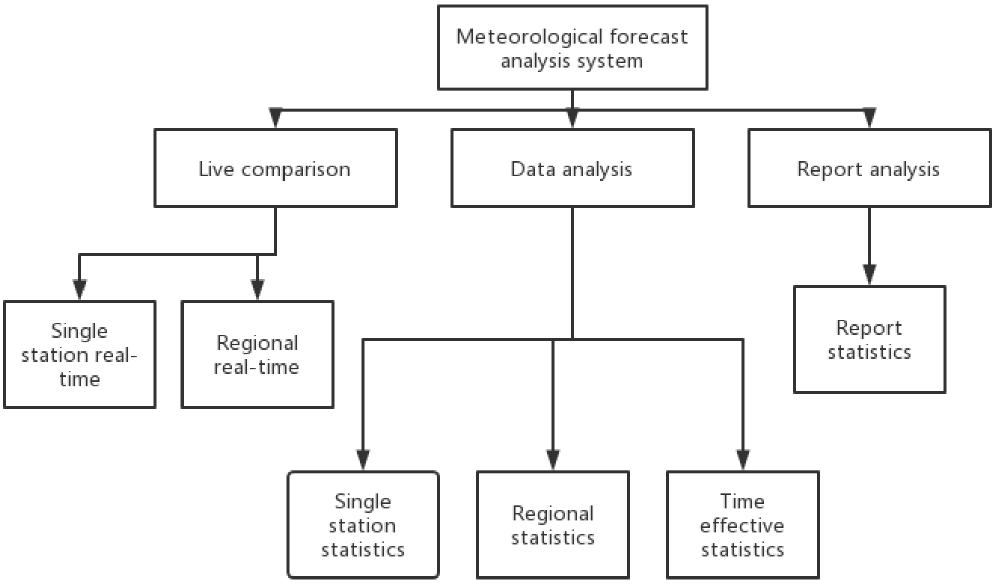

Figure 1. Overall structure of the meteorological data analysis system

The real-time comparison module is a data comparison module used to assist the weather forecast. It includes two parts: single-station real-time and regional real-time. The real-time requirement of a single station is to display the full-time forecast results of each model of the current start time of the selected area according to the start time, and it is required that the time limit must be converted into the corresponding time, such as the start time of 2015-10-1 08:00 , the time limit is 3, 6... Then, the time will be converted into 2015-10-1 11:00, 2015-10-1 14:00, etc. In addition, if the time point obtained by adding the time of reporting and aging is later than the current actual time, the live observation result should also be displayed. The actual requirement of the area is to display the forecast results of the directly-administered area under the selected area of each model according to the starting time of the report and the selected time limit. The data analysis module is a module that performs statistical analysis on meteorological historical data according to various elements and outputs the results, including three parts: single station statistics, regional statistics and aging statistics. Single-station statistics requires that the time period be taken as the X-axis, and each indicator is calculated and output according to the stations represented by the selected area, the selected statistical interval, and the selected analysis items.

Regional statistics requires that the first-level administrative area of the selected region is taken as the X-axis, and each indicator is calculated and output according to the selected time period, the selected statistical interval, and the selected analysis item. The aging statistics require that the aging is used as the X-axis, and the calculation results of each indicator are calculated and output according to all the stations under the jurisdiction of the selected area , the selected statistical interval, and the selected analysis item. Report generation only includes a module of report statistics, which requires the corresponding data calculation results to be produced according to the selected elements, and then displayed in the form of reports. The elements it needs to select include: region, time period, time, station type and forecast model [17-18].

3. Research Design Experiments for Optimal Analysis of Weather Forecast Supporting Convolutional Neural Networks

3.1. Database Structure Design

Through demand analysis, we get the data objects that the database needs to serve. However, how to abstract the database structure from the demand analysis is the top priority of database design. Common approaches to database design can be divided into three categories: top-down, bottom-up, and incremental expansion.

The top-down approach is carried out by means of the whole and then the refinement. First, the overall framework is completed, and then it is continuously enriched and refined. The bottom-up approach is just the opposite. It is achieved by first satisfying local requirements and then integrating them. The partial expansion method is somewhat similar to the top-down method. He designs the core content first, and then continuously expands the requirements on the basis of the core according to the needs, so as to obtain a complete database design.

3.2. Experimental Design

This paper first analyzes the meteorological data analysis algorithm constructed in this paper and the traditional data analysis algorithm for the same batch of meteorological data, and analyzes the data analysis accuracy of the two algorithms. The second is the score comparison between the convolutional neural network and the optical flow method for future short-term weather forecasting.

4. Experimental Analysis of the Optimization Analysis of Meteorological Forecast Supporting Convolutional Neural Network

4.1. Algorithm Performance Comparison

This paper analyzes the logs generated by the automatic analysis system of meteorological messages, and organizes the daily processing data information as follows: The system starts to process the new messages monitored on the day according to the timing strategy (0:00 to 3:00 a.m. every day), and processes different meteorological elements. The amount of messages (the ground meteorological observation data A file, the automatic station Z file, etc.); the progress of the convolutional neural network is divided by comparing the performance of the two algorithms. The experimental data is shown in Table 1.

Table 1. Message-resolved experimental data

	Ground meteorological data	Automatic station data	Minutes of observation data
Traditional algorithm	95.62	97.31	98.12
In this paper, the convolutional neural network algorithm of the	99.71	99.68	99.84

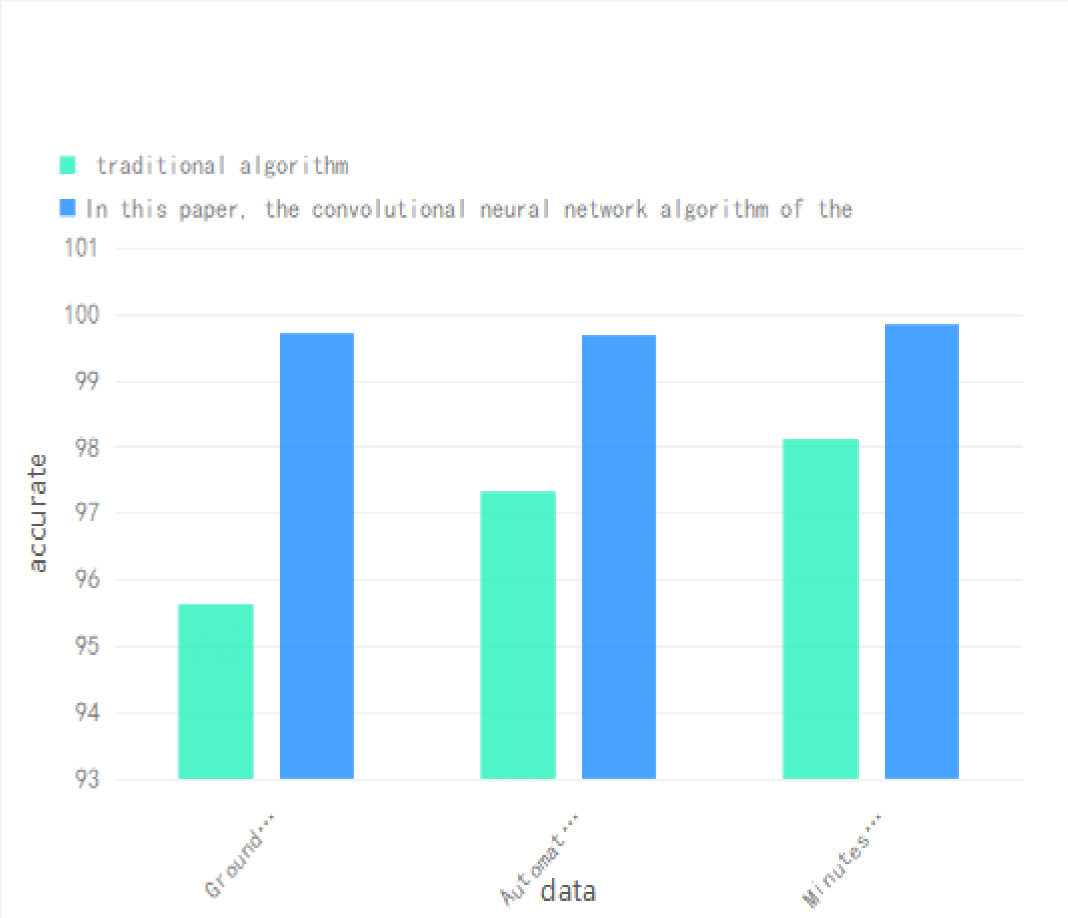

Figure 2. Comparison of the success rate of word resolution between the present algorithm and the traditional algorithm for the data

As can be seen from Figure 2, the algorithm in this paper has a higher accuracy of single data analysis than the traditional meteorological data analysis algorithm. Compared with the traditional algorithm, the data processing volume of the algorithm in this paper is also more. The accuracy rate will also be greatly improved.

4.2. Meteorological Short-Term Forecast

In this paper, six evaluation methods are selected for the prediction of the future short-term weather forecast by the ConvGRU model and optical flow method constructed in this paper. The experimental data are shown in Table 2.

Table 2. Average score of ConvGRU model and optical flow method in future 15 frames

	POD	FAR	CSI	RMSE	BIAS
ConvGRU	0.6342	0.2351	0.5472	4.5278	0.8659
Opticalflowmethod	0.6114	0.3468	0.5025	4.9592	0.88734

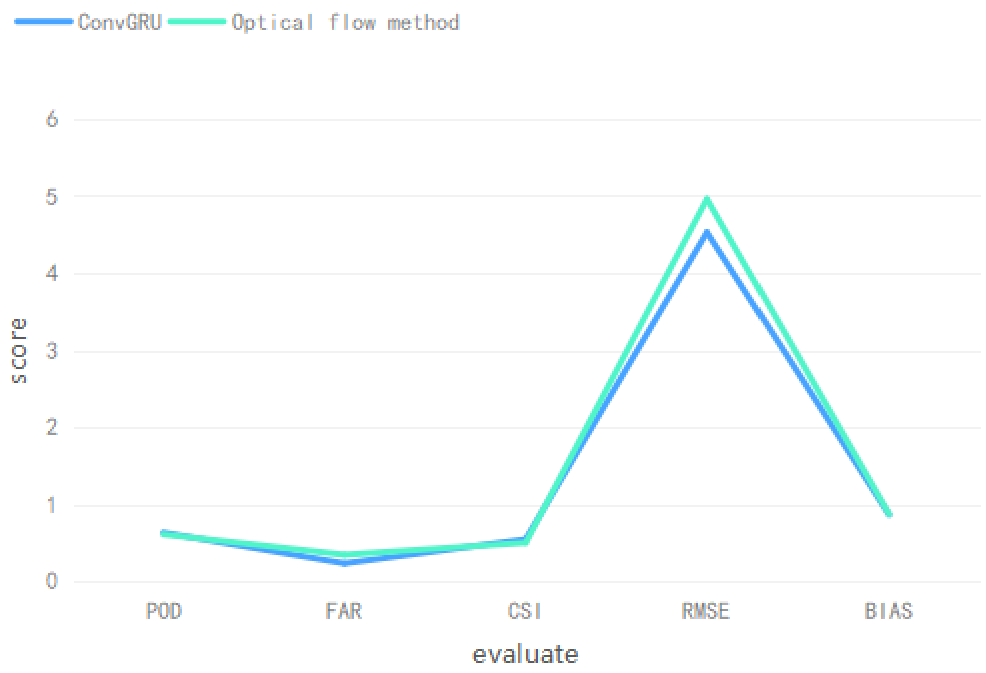

Figure 3. Scoring of short-term weather prediction by both algorithms

As can be seen from Figure 3, in general, the ConvGRU model has achieved relatively good performance, and is better than the optical flow method in the overall hit rate, especially in the FAR score. This may be due to the following reasons: (1) The ConvGRU model can handle boundary conditions well. In real life, it is often the case that a large number of clouds suddenly gather at the boundary, which may come from outside the echogram. If the neural network has encountered a similar situation during training, then after training, the neural network can give good prediction results. The optical flow method is difficult to deal with this problem. (2) The ConvGRU model uses the convolution structure for feature extraction, which can extract some complex spatiotemporal features from the data set, which are difficult to achieve by the optical flow method.

5. Conclusion

In view of the basic process of short-term precipitation forecast, this paper has done the following work in combination with the deep learning model: 1. Reviewing the previous research results in short-term precipitation forecast, after reading a lot of literature on neural network technology On the basis of , the convolutional neural network combined with the recurrent neural network is used to model the short and imminent precipitation forecast. 2. Image preprocessing. Before short-term precipitation forecasting, the radar echo data used to forecast precipitation needs to be preprocessed. The preprocessing process includes image grayscale, image cropping, and image denoising. Firstly, the conversion relationship between radar echo intensity and image grayscale is used to calculate the grayscale image of radar echo; then this paper compares various preprocessing methods. First, the image is cropped to obtain an effective image area. Then the image is filtered, and finally the input data set is obtained, which effectively reduces the training time of the network through preprocessing. 3. The convolution operation of the convolutional neural network is used in the feature extraction of the image data. The main idea is to reduce the number of parameters and reduce the spatial redundancy of the input data through the feature extraction of the convolutional neural network. 4. On the basis of the ConvLSTM network model, a ConvGRU model is proposed, which has a similar accuracy in short-term precipitation forecasting compared with the ConvLSTM network model, but can reduce the complexity of the network structure and reduce the memory and time required for training. The validity of the model is verified by comparing the short-term and imminent forecast results of precipitation with optical flow method. In summary, in this paper, the GRU model is applied to solve the problem of short-term precipitation forecasting, and the convolutional neural network and the GRU network are combined to obtain the ConvGRU model, which takes into account the spatial information contained in the input sequence, and finally effectively improves the short-term precipitation. forecast effect.

Funding

This article is not supported by any foundation.

Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

References

[1] Hewage P, Trovati M, Pereira E, et al. Deep learning-based effective fine-grained weather forecasting model. Pattern Analysis and Applications, 2021, 24(1):343-366. https://doi.org/10.1007/s10044-020-00898-1

[2] Zhou K, Zheng Y, Li B, et al. Forecasting Different Types of Convective Weather: A Deep Learning Approach. Journal of Meteorological Research, 2019, 33(5):797-809. https://doi.org/10.1007/s13351-019-8162-6

[3] Yi K, Moon Y J, Lim D, et al. Visual Explanation of a Deep Learning Solar Flare Forecast Model and Its Relationship to Physical Parameters. The Astrophysical Journal, 2021, 910(1):8 (11pp). https://doi.org/10.3847/1538-4357/abdebe

[4] Landa V, Reuveni Y. Low-dimensional Convolutional Neural Network for Solar Flares GOES Time-series Classification. The Astrophysical Journal Supplement Series, 2022, 258(1):12 (15pp). https://doi.org/10.3847/1538-4365/ac37bc

[5] Jeong S, Park I, Kim H S, et al. Temperature Prediction Based on Bidirectional Long Short-Term Memory and Convolutional Neural Network Combining Observed and Numerical Forecast Data. Sensors, 2021, 21(3):941. https://doi.org/10.3390/s21030941

[6] Sayeed A, Choi Y, Eslami E, et al. A novel CMAQ-CNN hybrid model to forecast hourly

surface-ozone concentrations 14 days in advance. Scientific Reports, 2021, 11(1):10891. https://doi.org/10.1038/s41598-021-90446-6

[7] Aprillia H, Yang H T, Huang C M. Short-Term Photovoltaic Power Forecasting Using a Convolutional Neural Network–Salp Swarm Algorithm. Energies, 2020, 13(8):1879. https://doi.org/10.3390/en13081879

[8] Liu G, Zhao H, Wang Z, et al. Performance Study and Multi-Objective Optimization of a Two-Temperature CO2 Refrigeration System with Economizer Based on Energetic, Exergetic and Economic Analysis. Journal of Thermal Science, 2022, 31(5):1416-1433. https://doi.org/10.1007/s11630-022-1696-4

[9] Yang Z, Si W, Zhao B, et al. Optimization of Meteorological Elements and Icing Prediction Based on Satellite-ground Data Fusion. Journal of Physics: Conference Series, 2021, 1966(1):012012-.https://doi.org/10.1088/1742-6596/1966/1/012012

[10] Mishra P K, Satapathy S C, Rout M. Segmentation of MRI Brain Tumor Image using Optimization based Deep Convolutional Neural networks (DCNN). Open Computer Science, 2021, 11(1):380-390. https://doi.org/10.1515/comp-2020-0166

[11] Shang L, Nguyen H, Bui X N, et al. Toward state-of-the-art techniques in predicting and controlling slope stability in open-pit mines based on limit equilibrium analysis, radial basis function neural network, and brainstorm optimization. Acta Geotechnica, 2022, 17(4):1295-1314. https://doi.org/10.1007/s11440-021-01373-9

[12] Jothiramalingam R , Anitha J, Hemanth D J. Diagnosis of coronary artery occlusion by fitting polynomial curve with the ECG signal based on optimization techniques. Network Modeling Analysis in Health Informatics and Bioinformatics, 2022, 11(1):1-14. https://doi.org/10.1007/s13721-022-00354-6

[13] Victor W, Somasundaram D, Gnanadason K. Adaptive particle swarm optimization–based deep neural network for productivity enhancement of solar still. Environmental Science and Pollution Research, 2022, 29(17):24802-24815. https://doi.org/10.1007/s11356-021-16840-9

[14] Meech S, Alessandrini S, Chapman W, et al. Post-processing rainfall in a high-resolution simulation of the 1994 Piedmont flood. Bulletin of Atmospheric Science and Technology, 2020, 1(2–4):1-13. https://doi.org/10.1007/s42865-020-00028-z

[15] Araguz C, Llaveria D, Lancheros E, et al. Architectural Optimization Framework for Earth-Observing Heterogeneous Constellations: Marine Weather Forecast Case. Journal of Spacecraft and Rockets, 2019, 56(3):1-13. https://doi.org/10.2514/1.A34182

[16] Oh M, Chang K K, Kim B, et al. Spatiotemporal Optimization for Short-Term Solar Forecasting Based on Satellite Imagery. Energies, 2021, 14(8):2216. https://doi.org/10.3390/en14082216

[17] Zhu Z, Yan H, Ng M K. The Use of Forecast Gradients in 3DVar Data Assimilation. Applied Mathematical Modelling, 2019, 74(OCT.):244-257. https://doi.org/10.1016/j.apm.2019.04.038

[18] Jamal A, Linker R, Housh M. Optimal Irrigation with Perfect Weekly Forecasts versus Imperfect Seasonal Forecasts. Journal of Water Resources Planning and Management, 2019, 145(5):06019003.1-06019003.6. https://doi.org/10.1061/(ASCE)WR.1943-5452.0001066