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AI-based intelligent virtual image meteorological services

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ABSTRACT

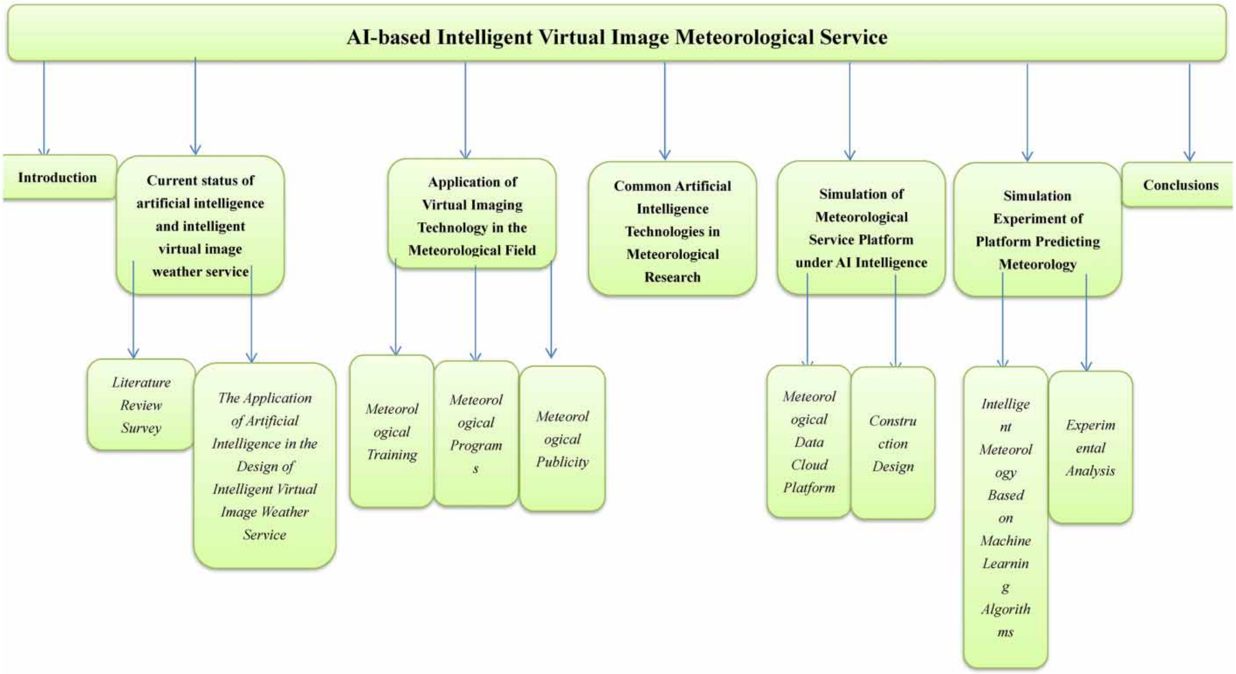
Although modern meteorological service and prediction systems have achieved good applications in numerical models, these models are often influenced by multiple random factors and cannot adapt well to the meteorological service and prediction needs of complex climate regions. Therefore, this article aims to designing an AI intelligent meteorological service platform to simulate what happens when people use it. Based on commonly used AI technologies in meteorological research, the temporal data algorithm mentioned in this article is used for prediction. This article selected the actual daily average water vapor pressure and daily average relative humidity data of three meteorological stations over the past 10 days for analysis. The maximum and minimum values of the actual daily average water vapor pressure in the 10 days of San Jose are 30.2 and 28.1 Pa, respectively, the maximum and minimum values of the actual daily average vapor pressure over 10 days of Cupertino are 30.4 and 28.4 Pa, respectively, and the maximum and minimum values of the actual daily average vapor pressure over 10 days of Santa Clara are 30.5 and 28.4 Pa, respectively, which can prove the effectiveness of AI-based intelligent virtual imaging meteorological services.

Key words: artificial intelligence, intelligent meteorology, intelligent weather service platform, machine learning, time-sequence data algorithms, weather services

HIGHLIGHTS

- Modern meteorological services and forecasting systems are susceptible to the influence of a variety of random factors and cannot well cope with the meteorological service and forecasting needs in complex climate areas.
- With the continuous development and maturity of artificial intelligence (AI) algorithms represented by neural networks, meteorological departments are trying to use statistical methods to replace or compensate for traditional numerical models. This article also designs an AI weather service platform based on this to simulate what will happen when people use it.
- This article selected the actual daily average water vapor pressure and daily average relative humidity data of three weather stations in the past 10 days for research and analysis, and found that the virtual imaging weather service system based on AI was more effective.

GRAPHICAL ABSTRACT



1. INTRODUCTION

At present, many regions have entered the information age, and with the continuous improvement of people's living standards, higher requirements have been put forward for the quality of meteorological services. In recent years, environmental issues have become increasingly severe and have had a significant negative impact on people's lives. Meteorological services are closely related to people's production and life. Accurate meteorological predictions and information can enhance people's awareness of disaster prevention and actively take disaster prevention measures, thereby reducing the adverse consequences of meteorological disasters. Therefore, in this context, meteorological services have been given new tasks, and relevant departments and technical personnel have utilized advanced technological means to optimize the process of meteorological services, thereby improving the quality and scope of meteorological services. On this basis, a new and suitable method for meteorological service forecasting in the current era urgently needs to be developed.

With social progress and economic development, the demand for meteorological services from various industries and individuals in society is constantly increasing, and the research and application of meteorological services have also attracted the attention of many scholars. Garcia-Marti believed that the National Meteorological Service is limited by actual and financial boundaries in terms of the number of official meteorological measurements it collects (Garcia-Marti *et al.* 2023). Zhu analyzed relevant literature from three dimensions: data collection, information analysis, and meteorological knowledge application in his research by focusing on papers and databases that promote or implement meteorological knowledge services through crowdsourcing methods (Zhu *et al.* 2020). Muita believed that the availability of meteorological data requires a good network of artificial weather stations and other support systems to collect, record, process, archive, communicate, and disseminate. It is very useful for various applications and departments, from weather and climate forecasting, landscape planning to disaster management (Muita *et al.* 2021). Mariotti outlined the knowledge base, progress, and recent plans of the Cross Agency Committee on Meteorological Services, including efforts to develop long-term strategies as a means of promoting community participation. The Inter-Agency Committee on Meteorological Services would continue to provide coordination for federal agencies and opportunities for input and participation for non-governmental entities. Developing a long-term strategy is a serious process carried out by the Inter-Agency Committee on Meteorological Services, and sustained external community participation is the key to healthy development and achieving results (Mariotti *et al.* 2023). Xu believed that cloud computing, as a powerful way, can provide resources for processing services of the industrial Internet of Things, such as the meteorological industry. Meteorological services, which usually have complex interdependent logic, are modeled as workflows (Xu *et al.* 2019). Zhang has constructed a big data meteorological service structure in a cloud computing environment, including meteorological services, meteorological survey services, and public meteorology (Zhang *et al.* 2019). The studies have achieved good results, but there are still problems such as limited empirical research on the application of meteorological services.

In recent years, with the development of artificial intelligence (AI) technology, combining it with the field of meteorological services has become an urgent task. Taherei Ghazvinei believed that traditional disciplinary methods cannot provide comprehensive management solutions for meteorological services, and AI methods based on system-wide analysis are crucial for bringing beneficial changes to the meteorological service industry and communities (Taherei Ghazvinei *et al.* 2018). El Ibrahimi aimed to predict meteorological conditions by using and comparing neural fuzzy adaptive inference systems, multilayer perceptron artificial neural networks, and support vector models (El Ibrahimi *et al.* 2018). The above research indicates that the application of AI in the field of meteorological services has a positive effect, but there are still issues such as immature technology. Kim described the development of an optimized corn yield prediction model under extreme weather conditions in the mid-west of the United States. Six different AI models were tested using satellite images and meteorological data to dominate the growth period, indicating that the optimized deep neural networks (DNN) model can provide a robust prediction of corn yield under extreme weather conditions (Kim *et al.* 2020). Dewitte believes that AI is an explosive growth field of computer technology that is expected to profoundly change many aspects of our society and can respond to challenging new needs in weather forecasting, climate monitoring, and inter-chronological forecasting (Dewitte *et al.* 2021).

Meteorological services are closely related to people's daily lives. Whether it is the choice of travel methods or scheduling, the information provided by meteorological departments can be used as reference and decision-making. Meteorological services improve people's comfort and quality of life. However, there may inevitably be some regional issues with meteorological services in different regions. People's understanding of meteorological services is still relatively backward, especially in the main sector of meteorological services for agriculture, which has a relatively backward way of thinking and cannot keep up with the needs of agricultural development (Krøgli *et al.* 2018). First, the accuracy and precision of weather forecasting are not high, and the prediction of future weather disasters is not accurate enough, resulting in the inability to take timely response actions in agricultural production; second, the current meteorological service products are too single and lack specificity, and cannot accurately respond to the meteorological disasters encountered. The general public also attaches great importance to weather forecasting work, and many people need weather forecasting work to determine their work priorities. The poor presentation of weather forecasts greatly affects the quality of integrated meteorological services.

In the process of development in recent years, AI technology is constantly developing and advancing, which has laid a good foundation and opportunity for the modern development of meteorology. This article analyzes the current situation of AI meteorological services and studies the application of virtual imaging technology in the field of meteorology. It simulates the meteorological service platform under AI to provide assistance to users who lack understanding. Finally, based on several commonly used AI algorithms, this article uses time series data algorithms to predict daily average water vapor pressure and daily average relative humidity data for three stations in a certain region. Large-scale meteorological data analysis and AI algorithms combined can provide more precise and highly accurate weather predictions, as well as timely meteorological warnings that allow people to take timely action and lower the risk of disaster. Weather data can be obtained and displayed in real time. Simultaneously, a realistic three-dimensional meteorological picture can be given by technological methods using virtual visuals, enhancing users' cognitive abilities and helping them notice and interpret meteorological changes more intuitively.

2. CURRENT STATUS OF AI AND INTELLIGENT VIRTUAL IMAGE WEATHER SERVICE

This article analyzes the current situation of AI meteorological services. First, some literature on AI applications in meteorological services was consulted online. This article found that there have been many losses of people and property caused by extreme weather conditions in previous years and compiled a list of key research directions and meteorological issues in the literature, as shown in Tables 1 and 2.

Applying AI to the research and prediction of meteorological science would generate enormous economic benefits. Sudden or extreme climate events pose significant risks to ecosystems, infrastructure, and human health (Leuenberger *et al.* 2020). Due to inaccurate weather conditions, many places have suffered incalculable direct economic losses. Although climate

Table 1 | Losses caused by extreme weather conditions

	Human casualties (person)	Urban damage degree (%)	Farmland damage degree (%)	Direct economic losses (10,000)
2018	6,854	15	27	78,546
2019	7,416	14	23	84,569
2020	4,584	17	24	67,854
2021	5,874	12	21	78,231

Note: The data are sourced from publicly available online data.

Table 2 | Number of literature on various meteorological service research directions

	Meteorological prediction and recognition	Short-term meteorological forecast	Quantitative precipitation forecast	Typhoon ensemble forecasting
2018	10	7	6	2
2019	8	13	4	2
2020	5	14	3	1
2021	5	15	2	3

change is inevitable, early warning can reduce some economic losses. Traditional meteorological models often have significant shortcomings in predicting unexpected events. Therefore, the use of AI to achieve meteorological model prediction has a certain application value. In addition, in meteorological data processing, AI technology can be used to improve data processing efficiency while also reducing the workload of cartographers and forecasters. In different industries such as wind power generation, agriculture, and environmental monitoring, AI can also save costs and improve management efficiency by improving prediction accuracy.

2.1. Literature review survey

Here, a total of 110 literature works from 2018 to 2021 were reviewed through CNKI (China National Knowledge Infrastructure), excluding some literature that is relatively unrelated to the research direction. The remaining 100 articles are all related to meteorological prediction and recognition, short-term meteorological forecasting, quantitative precipitation forecasting, and typhoon ensemble forecasting.

Long ago, meteorologists conducted research on the application of AI in meteorological services and proposed important research directions. The meteorological services provided by the meteorological bureau require image recognition and analysis technology based on meteorological observation work. It uses image recognition to process images, information, and data collected by monitoring devices and converts them into weather analysis data for weather conditions such as rain, snow, and fog. Obtaining this information through meteorological monitoring devices can reduce the cost of monitoring devices. The main reason is that many observational data are of high density and large span, so their processing results are somewhat related to their own integrity. Data processing and the application of computer technology are inseparable. It can integrate massive amounts of data using computer technology and has strong processing capabilities for various types of data. It can be analyzed that the current situation is that the distribution of meteorological stations in many cities is uneven and difficult to adapt to the needs of urban development.

In addition, due to the complex terrain conditions of each region, there have been situations where weather observation devices cannot adapt, resulting in low data integrity. The observation of short-term meteorological data is closely related to human daily production and life and directly affects human travel work. Therefore, short-term weather forecasting is the most commonly used meteorological service for the public (Alley *et al.* 2023). A study has analyzed a short-term temperature and precipitation prediction method that can combine radar technology with neural networks. Through big data processing technology, user behavior characteristics can be extracted and user browsing trajectories analyzed, aiming to promote targeted meteorological services. This information can be obtained through highway monitoring devices, and the cost of monitoring devices can be reduced. Data processing, also known as data cleaning and data integration, is closely related to the application of computer technology. It can utilize computer technology to integrate massive amounts of data and has strong processing capabilities for various types of data.

2.2. The application of AI in the design of intelligent virtual image weather service

Optimizing and transforming traditional meteorological service products through the integration of AI technology and meteorological services can significantly improve the service quality and performance of meteorological products.

2.2.1. Technical support

AI technology and other emerging technologies are constantly innovating and developing, which provide technical guarantees and support for the development of the meteorological service industry. At present, the national meteorological department and various institutions are constantly collaborating with each other, conducting in-depth research on software development and big data integration technology and achieving some results. At the same time, the application of AI to the field of meteorological services is also a new development direction, and many cities have launched a series of research work.

The estimation and optimization of the weights will directly affect the combined results of the prediction results of the basic model for different features and calculate the combined weight coefficient:

$$\min H = M^T E M = \sum_{i=1}^{T} \sum_{j=1}^{n} m_i m_j \tag{1}$$

where $M^T EM$ is the value of the prediction error of the column vector.

In the constructed AI algorithm, combined with the optimization process of the chicken swarm optimization (CSO) algorithm and combining the connection weight with the operation of the wavelet coefficient, a new iterative method is constructed:

$$h_{\text{objective}} = \frac{1}{m} \sum_{i=1}^{m} [(W_i - W_i^{\text{train}})^2 + (F_i - F_i^{\text{train}})^2] \tag{2}$$

where m is the total sample amount of the training set, W_i is the upper limit of the training set, and F_i is the lower limit of the training set. W_i^{train} and F_i^{train}correspond to the fitting results of W_i and F_i, respectively. Optimization stops when the maximum number of iterations is reached.

2.2.2. Meteorological information services

Nowadays, society has fully entered the information society era, and the transformation from small data to big data has had a huge impact on people's lifestyles and production methods. The application of AI in meteorological service design can help people reduce natural disasters and protect people's lives and property. A meteorological service platform can be created through AI of meteorological data, and AI services are becoming an open and shared environment, achieving a reasonable global big data business organization. The connection and cooperation between local and institutional authorities have established a strong meteorological information service system. It has done a lot of work in the fields of meteorological monitoring, meteorological service management, and meteorological research and development, making significant contributions to the establishment of intelligent meteorological service systems and the development of meteorological services (Zsoter *et al.* 2019).

3. APPLICATION OF VIRTUAL IMAGING TECHNOLOGY IN THE METEOROLOGICAL FIELD

By utilizing virtual imaging technology, various meteorological conditions can be simulated and restored to carry out disaster warnings, disaster prevention knowledge dissemination, and other work to the public, improving meteorological science popularization and publicity capabilities. This can effectively enhance the emergency management department's emergency capacity, which can be expanded in the following aspects:

3.1. Meteorological training

Meteorological knowledge is extremely complex, and it is difficult to establish corresponding mathematical models and simulate corresponding simulation environments based on the actual situation in the meteorological field in traditional teaching and training, which greatly restricts the development of meteorology teaching. After using virtual imaging technology, models can be highly simulated and restored for various meteorological phenomena, providing a solution for the lack of experimental equipment, venues, and even funding for meteorological teaching. At the same time, a meteorological model based on virtual imaging technology can be established, which can also lay the foundation for the teaching of meteorological equipment in meteorological training, guiding students to conduct experiments on orderly assembly and disassembly of equipment. The high degree of simulation between models and physical objects allows students to experience the real effects of simulated environments and business processes supported by devices and quickly master relevant technologies and applications.

3.2. Meteorological programs

With the development of virtual reality technology in film and television, the audience of meteorological programs also has higher requirements for meteorological programs themselves. They not only hope that meteorological programs can be broadcast in a timely and accurate manner but also hope to visualize and liven up the meteorological programs during the display process. Virtual imaging technology can be applied to meteorological columns, which can fully meet the needs of the audience and stimulate their own vitality, thereby improving the ratings of meteorological columns. In addition, virtual imaging technology can be applied to meteorological programs to enhance the readability of meteorological forecast displays, enabling viewers to better understand relevant meteorological knowledge and signs and promoting a shift from listening to watching.

3.3. Meteorological publicity

With the three-dimensional development of meteorological knowledge, users' cognitive preferences have been improved. In the context of virtual imaging technology, most users have put forward higher requirements for relevant meteorological science popularization and promotion. Especially, the main body of meteorological science popularization and promotion is usually teenagers. Integrating virtual imaging technology into it can help teenagers better understand and master knowledge and phenomena in the meteorological field. For example, three-dimensional virtual imaging technology can be used to simulate the visual and sound effects of wind, clouds, lightning, etc., and combined with interactive technology in information technology, it can enhance the sense of the presence of teenagers in learning. At the same time, it can also help them have a deeper understanding of meteorological knowledge and contribute to their future development.

With the integration and development of virtual imaging technology and meteorological services, traditional meteorological service products have been continuously optimized and transformed, greatly improving the quality and efficiency of their services. Therefore, research on virtual imaging technology for meteorological services is gradually unfolding in many regions.

4. COMMON AI TECHNOLOGIES IN METEOROLOGICAL RESEARCH

This article utilizes AI technology to analyze meteorological services and categorize meteorological service projects, extending them to independent fields to explore the relevant technologies they utilize. This article hopes to draw on some experience from the effectiveness of its methods and apply it to the following text. Here, the commonly used AI technologies in meteorological research are summarized in Table 3, and some commonly used technologies are discussed.

Computer vision refers to the use of cameras and computers to replace human eyes in identifying, tracking, and measuring targets, followed by image processing and computer processing to make them more suitable for human eye observation or transmission to instruments for detection. Weather forecasting is a computer vision problem that converts radar data into images, treating weather forecasting as a series of images to infer weather changes.

Convolutional neural networks consist of one or more neural network nodes that are all interconnected. Compared with other deep learning frameworks, convolutional neural networks can achieve better image and sound recognition results and can use backpropagation algorithms. Compared with other deep and feedforward neural networks, convolutional neural networks require fewer parameters, which is a very potential deep learning architecture.

Long short-term memory (LSTM) network is a recurrent neural network that takes a time series as input, recurses the sequence in the direction of time evolution, and forms a chain relationship between nodes. LSTM is currently the most popular recurrent neural network, which overcomes the shortcomings of traditional recurrent neural networks and has been widely applied in many fields. It is mainly applied to speech recognition, image description, natural language processing, and other fields.

Table 3 | Common artificial intelligence technologies in meteorological research

	Meteorological service category	Area	Related technologies	Advantage
1	Data service	Data analogy Data feedback	Long short-term memory network Neural network	Strong correlation
2	Climate services	Climatic classification Climate recognition	Machine learning Convolutional neural network	High accuracy
3	Predicted service	Temporal prediction Regional prediction	Long short-term memory network Convolutional neural network	High predictive power
4	Condition services	Temperature conditions Extreme meteorology	Long short-term memory network Computer vision	Linear relationship
5	Weather services	Thunderstorm weather Blizzard weather	Machine learning Machine learning	Stability

It is not easy to find a stable model with good performance in all fields in supervised machine learning algorithms. In many cases, only a few weakly supervised models with good performance can be obtained. Machine learning fuses multiple weakly supervised models to obtain a more complete strongly supervised model.

Virtual imaging weather services, satellite images, or radar images are often used for analysis and prediction. AI methods in image processing include image segmentation, object detection, image enhancement, etc., which can help to extract and analyze specific features and patterns in meteorological images. Machine learning algorithms are used to train and optimize the models to achieve the prediction and simulation of meteorological data. Common machine learning methods include the decision tree, support vector machine, random forest, and so on.

In meteorology, most data are time series data, and the characteristics of time series data can be used to better predict future meteorological conditions. The basic idea of the algorithm is to use relevant mathematical models to describe a set of regular time series data formed over time and then use this model and the past and present values of the time series data to predict future values.

The zero conversion process means that the data sequence has a mean of 0:

$$\mathrm{zero}(i) = \mathrm{src}(i) - E(\mathrm{src}) \tag{3}$$

The variable E can be expanded as follows:

$$Ex_t = \frac{1}{n}\sum_{t=1}^{n} x_t \tag{4}$$

Pattern recognition refers to determining which model a stationary sequence is suitable for and preliminarily determining the order of the model, that is, determining the Y and t values and calculating the autocorrelation and partial autocorrelation coefficients of the sequence. The operation process of pattern recognition is relatively complex, and its judgment is based on the sample average, autocorrelation coefficient, and partial autocorrelation coefficient of the stationary sequence. The formula is

$$\widehat{\rho}_k = \frac{\sum_{t=1}^{n-k}(Y_t - \bar{Y})(Y_{t+k} - \bar{Y})}{\sum_{t=1}^{n}(Y_t - \bar{Y})^2} \tag{5}$$

Among them, k is the delay time, $\bar{Y}$ is the average of the sequence, and the autocorrelation coefficient refers to the correlation between two items in the time series after being separated by k. Its value is $-1 \leq \hat{\rho}_k \leq 1$. If $\hat{\rho}_k$ is closer to 1, the correlation is stronger, and if the distance is farther, the correlation is weaker.

Under certain conditions, the partial autocorrelation coefficient is a sequence, ϕ_k, and its expression is

$$\varphi_k = \begin{cases} \hat{\rho}_1 \\ \hat{\rho}_k - \sum\limits_{j=1}^{k-1} \hat{\varphi}_{k-1} \\ 1 - \sum\limits_{j=1}^{k-1} \hat{\varphi}_{k-1} \end{cases} \tag{6}$$

It can screen the degree of deletion of autocorrelation coefficients and partial autocorrelation coefficients in the time series and explore the order of the model.

5. SIMULATION OF METEOROLOGICAL SERVICE PLATFORM UNDER ARTIFICIAL INTELLIGENCE

AI meteorological services can effectively integrate meteorological information among industries, thereby extending meteorological services to various fields and enabling the sharing of meteorological data resources. In order to adapt to the diverse development of society and have high requirements for various aspects, AI meteorological services have become inevitable. The development of the power system is closely related to meteorological, environmental, and other factors, and changes in meteorological conditions would have adverse effects on the operation of the power system, causing faults in the power system. In this context, studying AI meteorological services can provide diversified and personalized services for the intelligent development of the power system, ensuring the safe operation of the power system. Based on the above research, this article analyzes the network architecture of a meteorological service platform based on AI, as shown in Figure 1.

5.1. Meteorological data cloud platform

All data from the meteorological data platform come from urban meteorological observation stations, satellites, radar monitoring, etc. In the process of building a meteorological data cloud platform, deep learning methods can be used to achieve short-term weather forecasting in the future, thereby improving the accuracy and refinement of meteorological forecasting (Nipen *et al.* 2020). At the same time, AI algorithms can also be used to improve the production efficiency of meteorological forecasting and meteorological disaster warning information. It can timely release one-click information for specific populations, providing fast, timely, and accurate meteorological forecasting information for departments such as transportation, agriculture, and power.

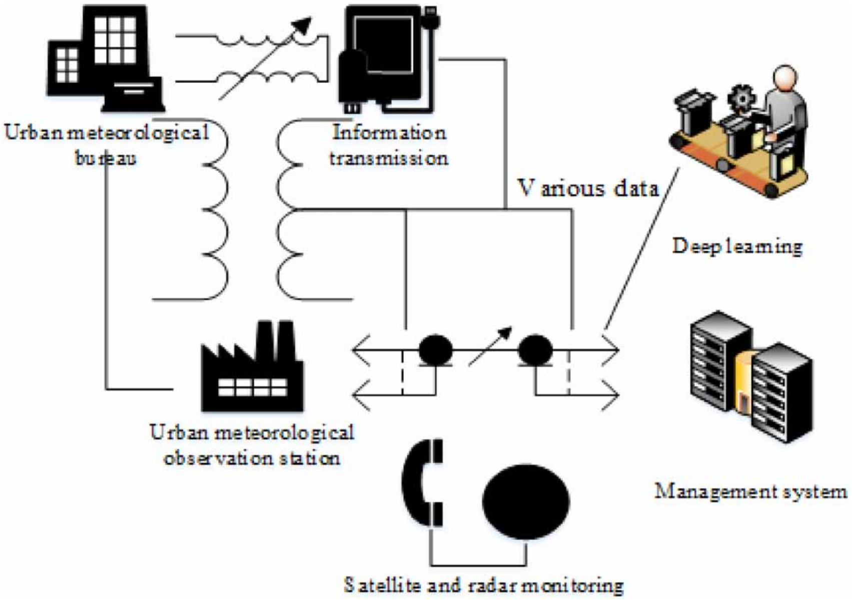


Figure 1 | Architectural design of AI meteorological service platform.

5.1.1. Meteorological prediction

The platform can monitor and upload meteorological data in real time to improve the accuracy of weather forecasting (Barszcz *et al.* 2018). By constructing a refined meteorological early warning analysis model, meteorological charts and climate characteristics can be analyzed and combined with regional characteristics. Comprehensive analysis of regional meteorological historical data can be conducted to grasp climate characteristics and change patterns in order to make more accurate predictions of future climate change trends. The AI platform used for meteorological services is aimed at predicting meteorological disasters, which can predict the location, time, degree, and degree of damage before the occurrence of meteorological disasters. It provides monitoring and evaluation services to assess the actual situation and potential trends of meteorological disasters in a timely manner.

5.1.2. Meteorological monitoring

This platform can also monitor the temporal data of various meteorological stations in real time and accurately, thereby achieving real-time and accurate forecasting of each meteorological station (Eyre *et al.* 2020). Given the sudden and ever-changing weather conditions, a video monitoring and sharing platform based on massive data information can be studied to achieve accurate forecasting of weather changes. Building a unified video resource monitoring system to transmit real-time monitoring videos on the basis of geographic information, a public service platform can improve the accuracy of severe weather prediction.

The meteorological department can also use video surveillance resources to analyze and utilize meteorological data. The optimal physical parameter scheme can be studied based on the geographical and climatic characteristics of power lines, substations, and other areas, and quality control has been carried out for data collection and preprocessing. The AI meteorological service platform has the technological advantage of providing accurate forecasts, which can assist relevant departments in disaster prevention and control by predicting extreme weather conditions. Based on meteorological services, meteorological services can also be used in line planning to plan substation areas and power grid lines.

5.2. Construction design

The AI meteorological service platform in this article adopts a general distributed server architecture, and users can directly access the AI meteorological service platform through a browser. At the same time, a massive amount of meteorological environment information would be presented in visual form through web pages, and the user-friendly interface makes operation simpler. The meteorological service data required can be downloaded through various mobile terminals. The system includes a data transmission and processing module, an application server, and an information service platform display module. The data transmission and processing module can achieve real-time updates of meteorological service platform data and filter and correct all data. All data would be uniformly stored in the database and open to users. Administrators can access the database through identity authentication. Figure 2 shows the meteorological conditions of a certain area on that day.

The hardware system of the AI meteorological service platform consists of a meteorological achievement conversion and display platform, a forecasting product production and warning release platform, and a meteorological emergency command platform. The smart meteorological service cloud platform achieves data information transmission function through a 5G network. It includes forecast data, live data, and conventional meteorological information data. The forecast data refer to the meteorological forecast results of the power grid, which are processed through information technology and entered into the database (Gustafsson *et al.* 2018).

6. SIMULATION EXPERIMENT OF PLATFORM PREDICTING METEOROLOGY

6.1. Intelligent meteorology based on machine learning algorithms

For the field of big data machine learning, in recent years, with the development of computer science, many new methods have emerged in the field of machine learning, which can efficiently and quickly mine and analyze data and extract useful information from it. Among them, the field of machine learning is an important research direction, using a series of learners for learning and using certain rules to integrate various learning results in order to obtain a machine learning method with better performance than a single learner. For training data, by aggregating several individual learners through a certain aggregation strategy, a strong learner can be formed to achieve the goal of absorbing the strengths of others. It can be summarized as studying how to fuse and learn the results obtained from multiple models with slightly lower accuracy to obtain models with higher prediction accuracy.

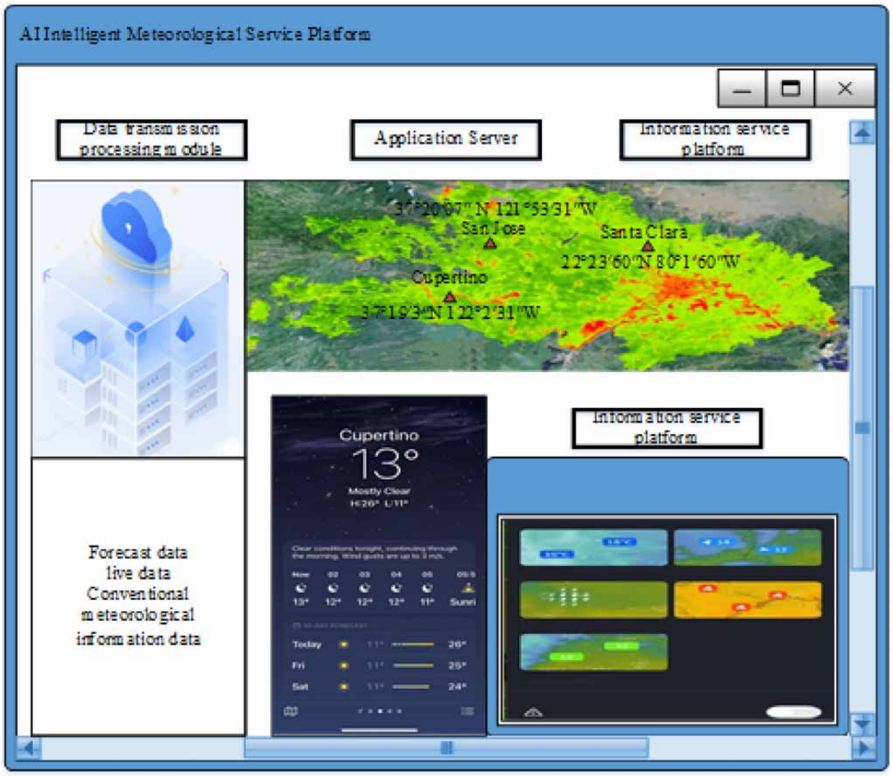


Figure 2 | AI meteorological service platform.

Another important research direction is the field of deep learning, whose core idea is to dynamically extract internal features from data through certain methods, thereby eliminating the dependence on human experience in traditional feature engineering methods and avoiding interference from external information. At the same time, these methods have stronger feature extraction capabilities compared with traditional methods in time series and spatial lattice-type data and can explore deeper levels of information. These new methods can be applied to historical forecasts of numerical forecasting and objective analysis of data at corresponding times. It can fully explore the regularity of errors in numerical forecasting within a certain time and space range, thereby correcting the errors of the forecast itself and obtaining higher accuracy prediction results (Kenyon *et al.* 2019).

Machine learning algorithms based on artificial intelligence can also fuse and analyze satellite data and radar echoes and perform deviation correction to obtain more accurate inversion data. By training the historical forecast data of numerical weather forecasting products, a deep learning model can be established. This can be achieved by matching the latest multimodal weather forecast products with corresponding live products as training samples, updating the parameters of the deep learning model, and selecting the optimal learning correction model through fusion. To ensure the accuracy of meteorological service data, it is necessary to perform secondary corrections on the forecast results to obtain high-precision short-term and imminent numerical forecasting products.

6.2. Experimental analysis

In this paper, one weather station in each of the three cities in Figure 2 is randomly selected to experiment on the actual daily average water vapor pressure and daily average relative humidity data in the past 10 days, using the timing data algorithm mentioned in this paper. In the timing data prediction algorithm, the final daily average water vapor pressure and final daily average relative humidity are predicted, and based on these two data, the daily average water vapor pressure and daily average relative humidity in the next 10 days are predicted. Finally, the predicted results are compared with the data of actual results. Figures 3–6 shows the actual and predicted daily average water vapor pressure values and daily average relative humidity values at the three sites in the past and next 10 days.

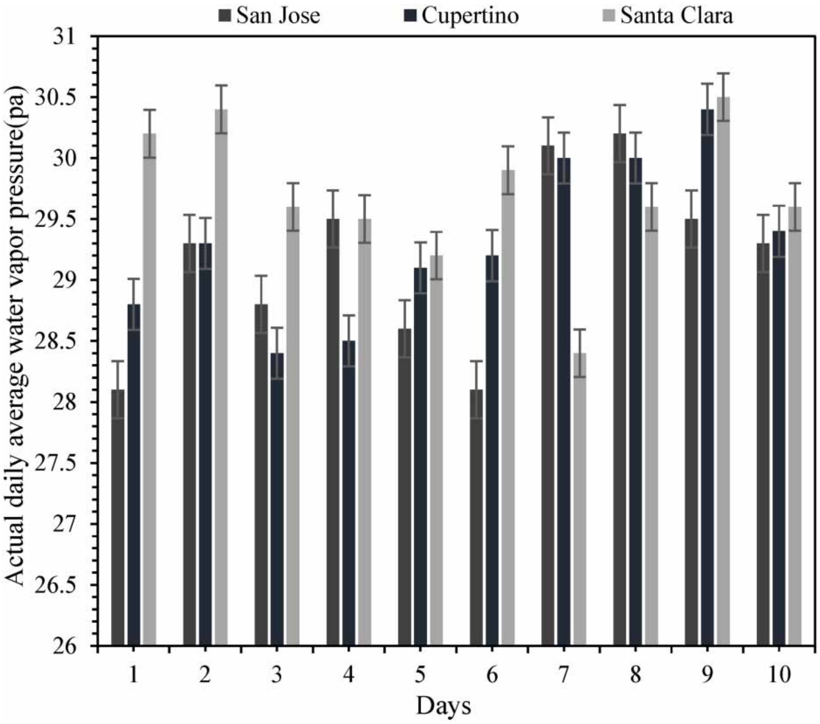


Figure 3 | Actual daily average water vapor pressure of three stations over the past 10 days.

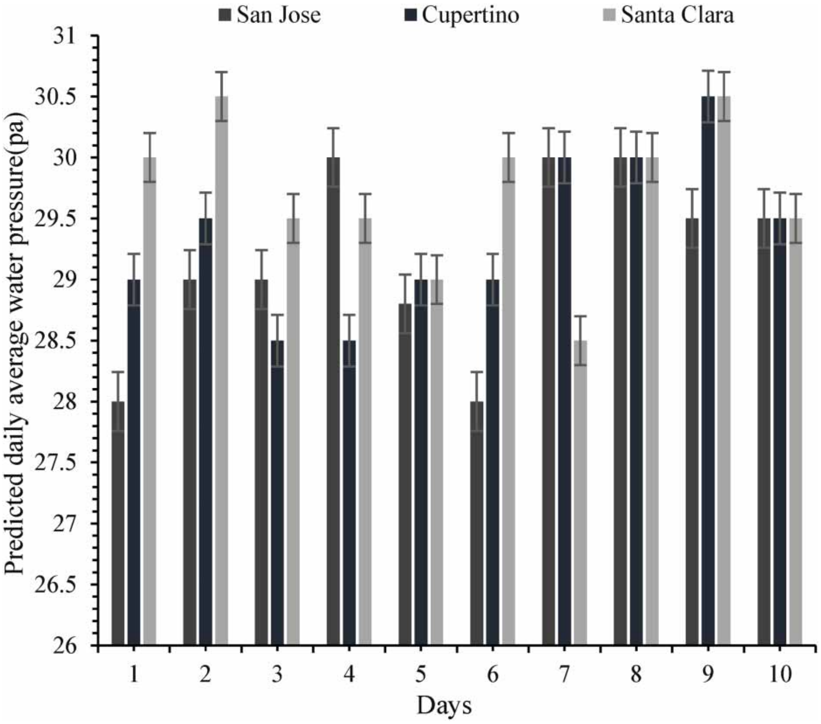


Figure 4 | Predicted daily average water vapor pressure of three stations over the next 10 days.

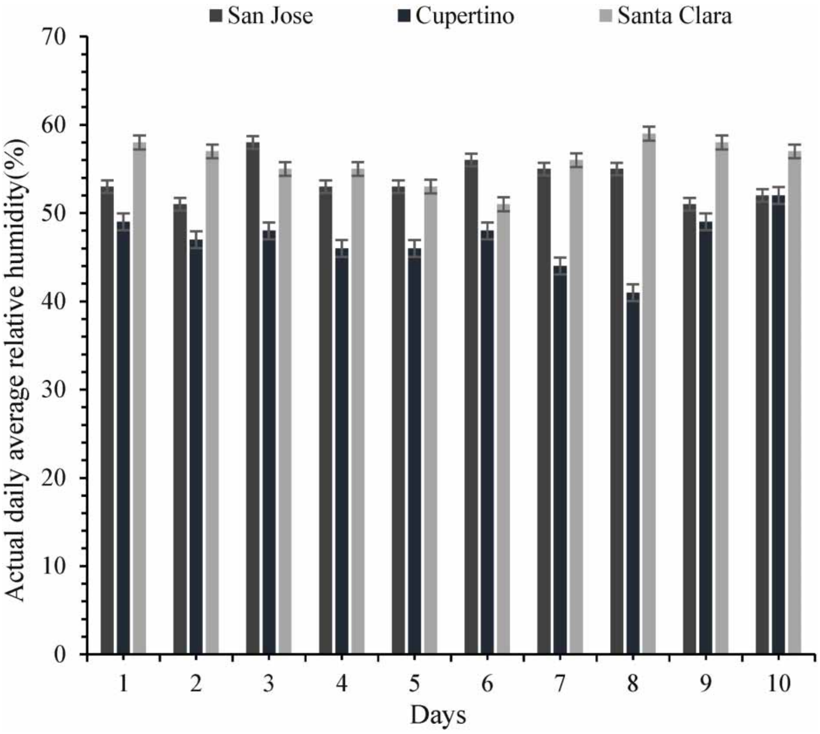


Figure 5 | Actual daily average relative humidity of three sites over the past 10 days.

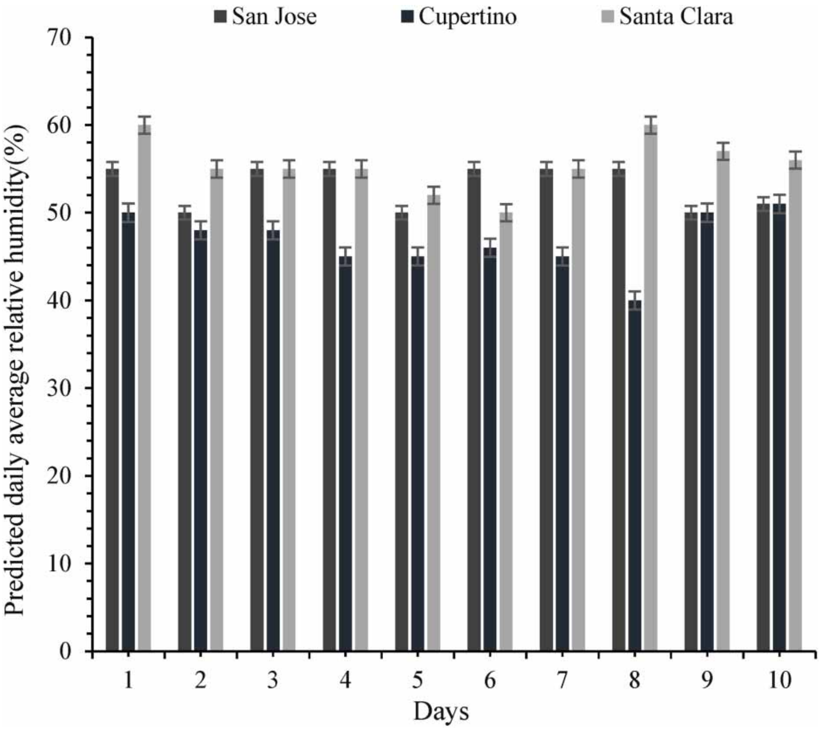


Figure 6 | Predicted daily average relative humidity of three sites over the next 10 days.

As can be seen from Figures 3 and 4, the maximum and minimum values of the actual daily average water vapor pressure in the 10 days of San Jose are 30.2 and 28.1 Pa, respectively; the predicted maximum and minimum values are 30 and 28 Pa, respectively. The maximum and minimum values of the actual daily average vapor pressure over 10 days of Cupertino are 30.4 and 28.4 Pa, respectively; the predicted maximum and minimum values are 30.5 and 28.5 Pa, respectively. The maximum and minimum values of the actual daily average vapor pressure over 10 days of Santa Clara are 30.5 and 28.4 Pa, respectively, while the predicted maximum and minimum values are 30.5 and 28.5 Pa, respectively. As can be seen from the figure, on the third day, the predicted daily average water vapor pressure in the three cities was the closest to the real daily average water vapor pressure, and the difference was statistically significant ($P < 0.05$).

It can be seen that the daily average water vapor pressure of the three stations is actually less different from the predicted maximum and minimum values.

As can be seen from Figures 5 and 6, the minimum and maximum actual daily average relative humidity values within 10 days of San Jose are 51 and 58%, respectively, whereas the predicted minimum and maximum values are 50 and 55%, respectively; the minimum and maximum actual daily average relative humidity within 10 days of Cupertino are 41 and 52%, respectively, while the predicted minimum and maximum values are 40 and 51%; the minimum and maximum daily average relative humidity values within 10 days of Santa Clara are 51 and 59%, respectively, while the predicted minimum and maximum values are 50 and 60%, respectively. It can be seen that the daily average relative humidity of the three stations in the area also differs slightly from the predicted maximum and minimum values.

Although many scientific research institutions and meteorological forecasting institutions have started using AI as a tool, there is still a lot of debate about its role in weather forecasting and meteorological services, and these debates are very valuable and worth exploring in depth. In meteorological forecasting services, there are thousands of factors that can affect weather changes, and any one of these factors is constantly changing (Kim *et al.* 2020). As the amount of data increases, AI requires more training data and computing power. In some places, even in numerical simulations, situations that AI cannot cope with may arise. If there is no premonitory weather, AI cannot be used to predict it.

7. CONCLUSIONS

China's meteorological business has entered a critical stage of transformation, with the meteorological service department serving as a key window for the meteorological department. This is due to the rapid growth of AI technology. To raise the caliber of meteorological services, the meteorological service department should be reformed before the meteorological department is reformed. Simultaneously, AI technology has advanced quickly in recent years and is now widely applied across numerous industries, raising the degree of industry informatization. From the perspective of the meteorological department, integrating AI technology can help the department grow and advance while also actively adjusting to the advancement of AI technology. AI technology is developing quickly. The transportation and meteorology industries have experienced significant expansion as a result of the advancement and integration of AI technologies in numerous industries. It cannot only offer fundamental assistance for the advancement and enhancement of diverse study topics in meteorology but also infuse fresh energy into the discipline's growth. This has the potential to significantly increase the meteorological disciplines' capacity to satisfy demands.

The following characteristics of an AI-based intelligent virtual picture weather service application may have certain limitations: (1) Handling of uncertainty: There are a number of uncertainties associated with meteorological changes, such as the intricacy of weather patterns, the features of meteorological data, and measurement errors. Although AI systems can process vast quantities of data and patterns, there are still difficulties in tackling meteorological uncertainty. Therefore, consumers must exercise caution and have a basic grasp of the prediction outcomes while using intelligent virtual picture weather services. (2) Data security and privacy: Using intelligent virtual image weather services may raise privacy and security concerns regarding people's location, time, and other critical information. Ensuring the confidentiality and integrity of user data is a critical responsibility that necessitates the implementation of appropriate data protection and privacy safeguards.

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DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

CONFLICT OF INTEREST

The authors declare there is no conflict.

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