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An Integrated Fishery Meteorological Information Service Terminal Based on End-Side Deep Learning Technology

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Abstract: Fishery meteorology has multiple impacts on the fisheries industry, especially in modern fishery industrial parks where renewable energy is extensively utilized. Therefore, this study developed a comprehensive fishery meteorological information terminal, based on the Android system, that considers the requirements of fish farming, fishery load, and the characteristics of renewable energy for fishery meteorology. This terminal aims to provide convenient and comprehensive information services to aquaculturists actively involved in modernizing the fisheries industry. The system consists of two main subsystems: the fishery subsystem and the weather subsystem. In the fishery subsystem, real-time monitoring and recording of fishery meteorology and related parameters can be achieved. In the weather subsystem, the demand for photovoltaic (PV) energy in weather forecasting is emphasized. A weather prediction model based on long short-term memory (LSTM) is used for hourly weather forecasting. The model is trained on meteorological station data by default, and users can also upload PV station data to obtain a model trained on such data. The system can retain two models simultaneously, and when one of the datasets is unavailable, the available data are used to make predictions on the corresponding model to ensure service stability. Additionally, we conducted experiments to verify the performance loss brought by deploying the model on the edge using TensorFlow Lite. The results show that when the memory usage is reduced to 1/33 of the original, the model still retains over 99% of its performance.

Keywords: fishery energy internet, meteorology sensitivity, fishery informatization, fishery load, deep learning

1. Introduction

In the process of aquaculture, due to the dependence of fish growth on the water environment and the sensitivity of the water environment to meteorological factors, we can observe some meteorological uncertainties that bring about uncertainties in the aquaculture process. Fishery meteorology has significant impacts on various stages of fish lifecycle in fish farming. For instance, temperature plays a crucial role in fish hatching rates, as demonstrated by Fu et al. [1]. Additionally, high temperatures can intensify bacterial proliferation in the water, leading to increased fish disease prevalence. Moreover, temperature can influence fish growth by affecting oxygen levels. Abdel-Tawwab et al. [2] found that oxygen levels during fish farming are influenced by multiple meteorological factors related to fisheries, including temperature, wind velocity, air pressure, and solar radiation. Insufficient oxygen levels in the water can be fatal to fish. Accurate monitoring and forecasting of fishery meteorology are crucial for timely responses to potential negative impacts. In recent years, researchers have made efforts to mechanize, automate, and modernize the fisheries industry. By employing devices such as feeders, pumps, and aerators, fish production efficiency has been improved, reducing the reliance on manual labor. However, fishery meteorology still exerts a significant and undeniable influence on fish farming. For example, although aerators maintain stable oxygen levels in the water and mitigate the impact of fishery meteorology, they do not eliminate its effects entirely. Adjusting the number of aerators indirectly mitigates the influence of fishery meteorology on the system. Fu and Gou [3] pointed out the unique meteorological sensitivity of fishery power load and formulated an all-encompassing model for power usage in fishery energy internet, demonstrating the effectiveness of the proposed model through measurements of electricity consumption per hectare per year and production per kilogram per year. Ensuring the proper functioning of these fishery machines is essential for the healthy growth of fish during the fish farming process. It is evident that fishery meteorology also impacts fishery load.

With the advancement of technology, modern aquaculture parks have overcome the limitations of traditional aquaculture in terms of scale and site by utilizing modern scientific technology and advanced equipment. However, this process has also introduced many meteorological sensitivity loads and energy supply methods that are highly sensitive to meteorological factors, such as photovoltaic (PV) energy that is temperature and radiation intensity. These newly introduced loads and energy supply methods are unavoidable for modern aquaculture to achieve green and efficient goals. Therefore, researchers focus on studying these meteorological factors that have a wide impact on modern

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aquaculture park systems, monitoring and recording such aquaculture meteorology, as well as predicting it, to ensure that current and future aquaculture systems can have corresponding strategies to cope with uncertainties. Fishery meteorology greatly influences the efficiency and electricity generation of PV energy systems, which have gained extensive adoption in the fisheries industry over the past few years. Fu [4] demonstrated that in fishery- PV complementary projects, high temperatures have a considerable influence on the performance of floating PV panels and accelerate their aging. Browne et al. [5] highlighted the constraints on PV power generation due to environmental factors such as temperature and solar radiation. Moreover, the PV power station environment is highly uncertain, as temperature, solar radiation, and other factors are influenced by weather conditions, resulting in significant uncertainty in PV power output. Zhang et al. [6] pointed out the instability caused by the extensive implementation of PV energy, which imposes negative impacts on the agricultural energy internet due to its intermittent nature. Fu et al. [7] emphasized the challenge of planning distributed renewable energy systems due to the influence of weather on them. Therefore, accurate weather forecasting is crucial to provide vital data support for future PV power forecasting and enable accurate estimation of PV power. Several studies have shown that weather forecasts provide valuable information for PV power forecasting. Sgarlato and Ziel [8] demonstrated that incorporating weather forecast results as external variables in autoregressive multivariate linear models can improve forecasting performance, especially when the autoregressive effect is weak. The accuracy of meteorological forecasts contributes to effective information for the model. In the research conducted, numerical weather forecasts were processed and input into a long short-term memory (LSTM) model to forecast future output [9]. The results showed that this approach enhances predictive performance. Browne et al. [5] revealed that solar radiation and temperature have a significant impact on PV power generation, making them the primary factors affecting electricity production. As a result, particular attention should be paid to temperature and solar radiation forecasting in weather forecasts.

To meet the diverse needs of modern fisheries in the context of the smart grid, and building upon the successful integration of artificial intelligence technologies with software development demonstrated in studies, we have undertaken the following work [10, 11]:

(1) Considering the impacts of fishery meteorology on fish farming, fishery load, and energy supply, as well as the resulting demand for fishery meteorological information services, we have developed a fishery meteorological information service terminal for the fishery energy internet. The terminal consists of two subsystems: the fishery subsystem and the weather forecasting subsystem. The fishery subsystem provides basic fish farming information, real-time monitoring and recording of fishery meteorology, as well as monitoring and recording of fishery load affected by fishery meteorology. The weather forecasting subsystem enables fishery meteorology forecasting, with particular consideration given to the demand for meteorology in modern fishery systems, such as the need for temperature and solar radiation forecasts.

(2) We have trained two sets of deep learning-based forecasting models, one based on meteorological station data and the other on PV station data. In cases where data for one set of models are unavailable, the other set of models can be used to ensure continuous availability of results.

(3) We have employed the TensorFlow Lite tool to lightweight the models and deployed them on the Android platform, allowing users to access them anytime and anywhere from their mobile devices.

The subsequent content of this paper consists of four main sections. Section 2 compares similar systems and technologies. Section 3 introduces the technologies employed in our proposed system and provides demonstrations. Section 4 conducts experiments on the deep learning models. Finally, Section 5 summarizes the work undertaken in this study.

2. Related Work

2.1. Other system

We conducted a search on the app marketplace using keywords such as "weather forecast" and downloaded the top apps, as listed in Table 1. Our research revealed that these apps are primarily designed for the general public and provide forecasts for temperature, weather conditions, wind speed, wind direction, and various weather indices. However, none of them include forecasting for solar radiation. These apps typically rely on numerical forecast data or perform post-processing on such data, with most of the processing and service

Table 1
Similar system (top apps published on the App marketplace)

APP name	Brief
Moji	Moji provides precise weather services at the latitude and longitude level based on leading professional technology and huge meteorological and user data
ZYZhundain	Accurate Weather supports weather forecast services for over 40,000 townships, providing precise forecasting for the weather around you
CaiYun	CaiYun provides precise weather services at the latitude and longitude level based on leading professional technology and huge meteorological and user data
Weather Forecast: Live Weather	Weather Forecast: The Live Weather APP provides current weather observations and detailed weather forecasts from around the world
Weather: Forecast and Radar Maps	The app is an ideal choice for individuals seeking real-time updates on the most recent weather conditions
Digital Fisheries	Digital Fishing can view personal information, navigation profiles, and fishing details, marking the transition of inshore fishing to digitalization
Smart Fisheries	Smart Fishery is a software that provides professional services specifically for fishery farming users, allowing them to view the indicator information of various fishponds and manage and control the farming equipment

These data are from Huawei AppGallery or Google Play.

deployment occurring on the server side. Therefore, the stability of the service depends on the stability of the servers and network. Additionally, when the service is disrupted, the apps often overlook the option to provide forecast results using an alternative approach. Hence, this study emphasizes the significance of fishery meteorology in the fisheries industry, and the minimum requirement for obtaining forecast results is the stable acquisition of sensor data. As long as historical sensor data related to meteorological parameters are available, future weather can be predicted, thereby ensuring higher service stability. Moreover, reducing network transmission can also help lower power consumption.

Furthermore, we conducted a search on the app marketplace using keywords such as “fishery” and found that apps in this category are not commonly available. The relevant apps are also listed in Table 1. Among them, the “Smart Fishery” app only provides information on pond water quality and weather forecasts, focusing on water quality records, input–output records, feeding records, and similar aspects, without taking into account variables like the weight of equipment or prevailing weather conditions.

2.2. Deep learning-based approach

Recently, deep learning algorithms have been widely concerned in many fields [12–14], and the research on meteorology is also gradually deepening [15, 16]. Haque et al. [17] have used multiple deep learning models to predict future temperatures and have shown in experiments that the GRU-LSTM model has the lowest root mean square error (RMSE), while the convolutional neural network (CNN) has the best computational performance. Additionally, experiments were conducted on datasets from multiple locations to demonstrate the robustness of deep learning models. In forecasting tasks affected by various meteorological factors, the selection and processing of features are crucial for forecasting methods based on deep learning. Espinosa et al. [18] pointed out that feature selection in methods based on deep learning is a challenging task. By selecting appropriate features to incorporate into deep learning models, more knowledge can be provided and forecasting performance can be improved. Phan et al. [19] conducted research on the preprocessing of historical data, including temperature and irradiance, in a numerical forecast dataset and made forecasting at an hourly resolution. The experimental results demonstrated the superior performance of the preprocessed data. Some studies also focus on weather types, which not only improve interpretability in modeling but also have a positive impact on the forecasting results of weather-related variables. Huang et al. [20] established different models based on five weather types: sunny, partly cloudy, cloudy, mostly cloudy with rain, and rainy, for PV power forecasting, achieving good forecasting results and validating them in actual PV systems. Using weather forecast data and historical actual power generation data, they derived a model for forecasting the PV power output one day in advance. The effectiveness of the proposed PV grid forecasting model was verified through practical application in a domestic PV power station with a capacity of 20 kW. Azizi et al. [21] found that multiple deep learning models including LSTM and CNN-LSTM were used to forecast the future temperature and solar radiation, and the results showed impact of relative humidity on the model’s forecasting accuracy.

To achieve sufficient early warning and guidance for the safe scheduling of PV power stations, multiple-step forecasting results are usually required. Traditional time series forecasting methods may encounter the problem of error accumulation and increased complexity in the forecasting process when facing multiple-step forecasting [22]. On the other hand, shallow machine learning methods generally perform well in fitting multiple input variables to a single forecasting variable, but they may not meet the requirements of multi-time scale fishery meteorological forecasting. Deep learning, as an effective method for multivariate and multi-step forecasting, has stronger fitting capabilities and can adapt to various input–output scenarios. Moreover, deep learning models usually have a concise structure, which has attracted widespread attention. Tran et al. [23] reviewed several deep learning techniques for temperature forecasting proposed in the past decade, mainly based on artificial neural network (ANN) models, including recurrent neural network (RNN) and LSTM, and the final results indicated that ANN models can serve as effective tools in temperature forecasting. Patil et al. [24] proposed CPSO-LSTM, which combines deep learning model and optimization algorithm, improving the accuracy of temperature forecasting. LSTM models are representative models of weather forecasting, so our system adopts the LSTM model for forecasting. Table 2 shows the survey results of deep learning-based weather forecasting in this study.

In summary, to achieve high accuracy in predicting hourly solar radiation and temperature for the next day, it is necessary to use deep learning models that can adapt to multivariate inputs and multi-step outputs. LSTM models are representative models in this category; therefore, our system adopts the LSTM model for forecasting.

3. Proposed Methodology

3.1. Overall system architecture

There are two subsystems in this system. One is the fishery subsystem, which primarily provides real-time information on fish

Table 2
Research status of deep learning-based approach

Ref.	Deep learning algorithm	Input variable
Yi et al. [16]	FusionNet	Pollutants, historical weather, and weather forecast
Cao et al. [15]	U-Net	Historical precipitation
Haque et al. [17]	LSTM, CNN, GRU, GRU-LSTM CNN-LSTM	Daily minimum and maximum temperatures
Phan et al. [19]	GRU	Temperature, solar radiation, precipitation, wind speed, air pressure, and relative humidity
Huang et al. [20]	RBFNN	The weather forecast for the next day
Tran et al. [23]	RNN, LSTM	Precipitation, humidity, wind speed, air pressure, etc.
Patil et al. [24]	CPSO-LSTM	Daily minimum and maximum temperatures
Azizi et al. [21]	CNN, GRU, CNN-LSTM, LSTM	GHI, air temperature, surface pressure, RH

farming, the load of the fishery power system, and energy supply information. The other subsystem is the weather forecasting subsystem, which not only provides basic meteorological services but also utilizes LSTM technology deployed on the edge to deliver stable hourly forecasting for future one-day solar radiation and temperature. Figure 1 illustrates the main interface and workflow of the system. The LSTM model is implemented and trained using the TensorFlow framework and deployed on the Android system using TensorFlow Lite. Network communication is supported by the okhttp3 framework.

TensorFlow. A workflow has been provided to efficiently complete the training and inference process of deep learning models, enabling easy deployment of models on both server-side and various edge devices. The training and deployment process based on TensorFlow is illustrated in Figure 2.

OkHttp3. The widely used third-party library for network operations in Android development.

TensorFlow Lite. It is a simplification of TensorFlow that enables TensorFlow model inference on edge devices. It has features such as lightweight and high performance. Research by Li [25] indicates that in the context of mobile speech recognition, it achieves comparable results while reducing the model size on the edge device to only 0.00007 times the size of the server-side model, significantly reducing the model's footprint. Deploying a model using TensorFlow Lite involves five steps: The first step is training and saving the model. In a Python environment, the model is trained using the TensorFlow framework on a high-performance computer and saved as a TensorFlow (tf) format model. The second step is format conversion. The tf format model is converted to the TensorFlow Lite (tflite) format using the Conversion tool provided by TensorFlow Lite. The

Figure 1
APP demo of fishery weather

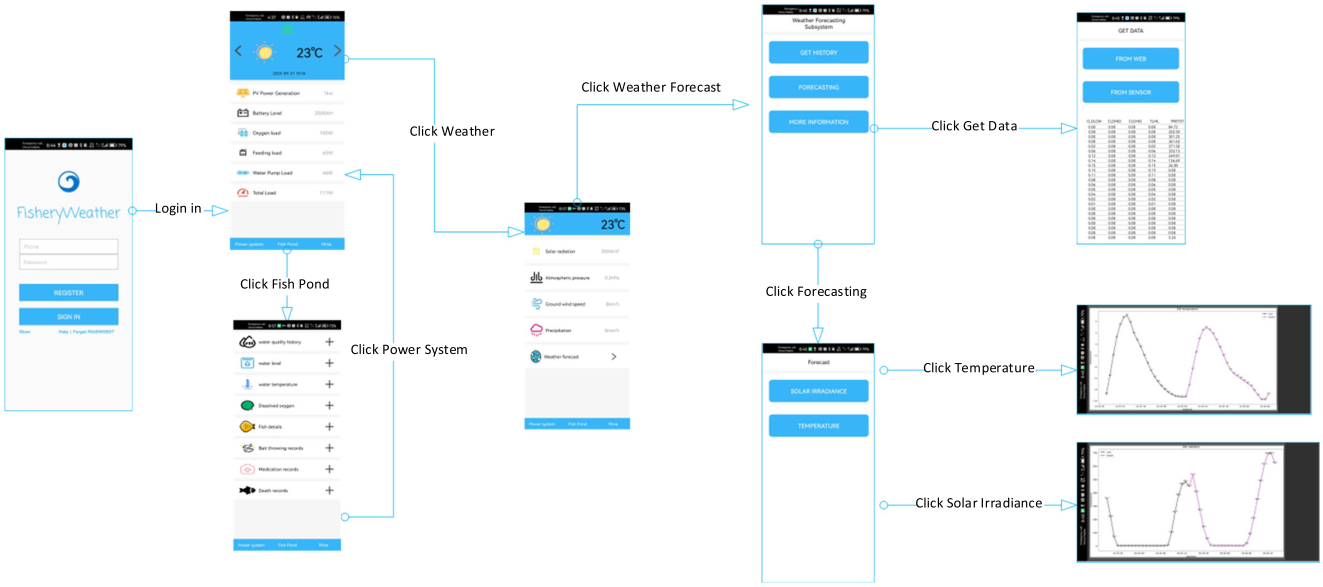


Figure 2
Flowchart of training of LSTM model

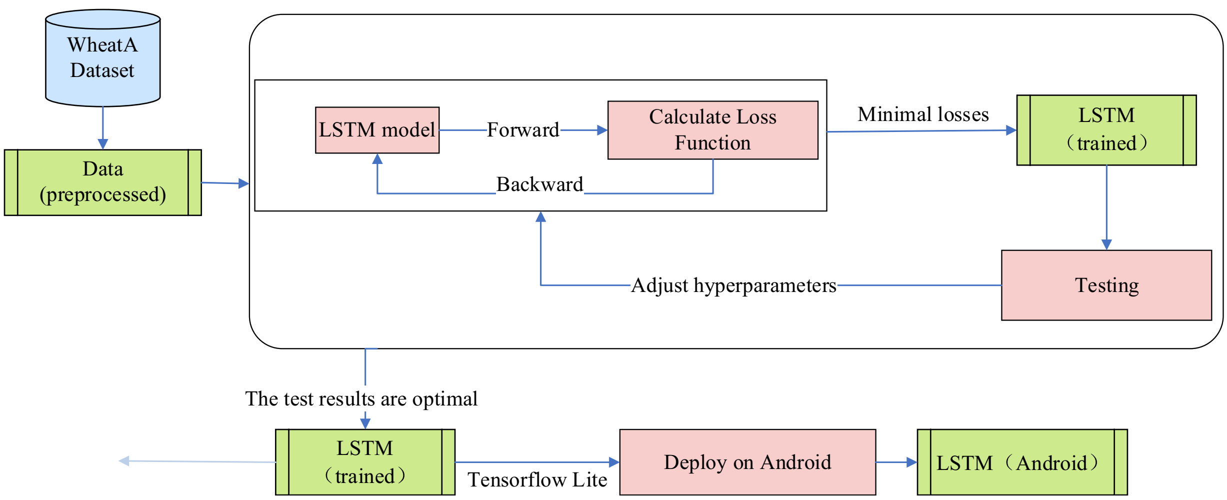
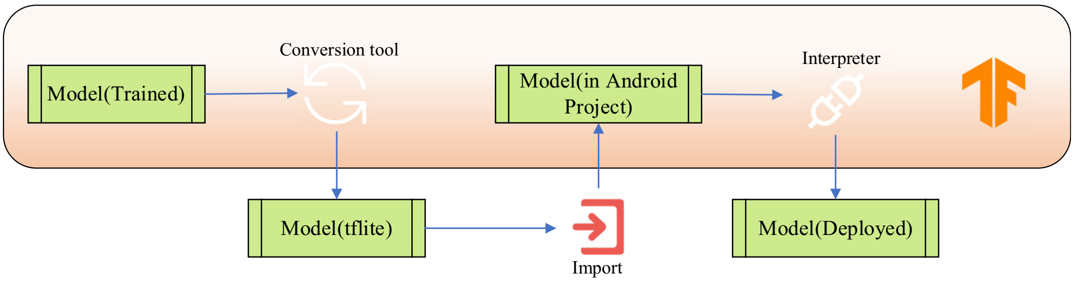


Figure 3
Deployment flowchart

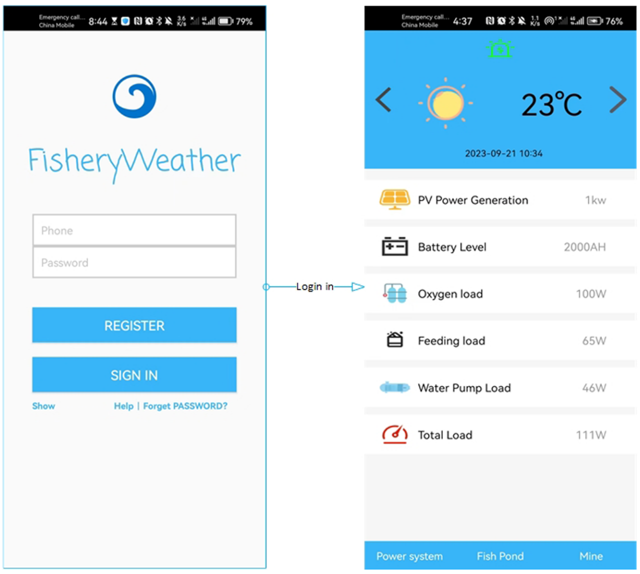


third step is importing the model into an Android project. The model is placed in the assets directory for later use. The fourth step is loading and using the model. The TensorFlow Lite dependency library is imported, and the tflite model data are converted into a MappedByteBuffer format. The TensorFlow Lite Interpreter is used to perform inference on the edge device. At this point, input data are provided in the format specified by the model to initiate the inference process. Figure 3 illustrates the deployment process.

3.2. Fisheries subsystem

After entering the correct username and password in the login interface as shown in Figure 4, users can access the first page of the fishery subsystem. This page displays basic information about the fishponds, including the types and quantities of fish, as well as medication and mortality statistics. Additionally, it presents various parameters of the aquaculture environment, such as water quality, water level, oxygen content, and infiltration rate of the pond soil.

Figure 4
APP diagram of the fish pond part of the fishery system



By clicking on the power system option below, users can enter the second interface, as shown in Figure 5. The top section of this interface displays the weather type, temperature, and date for the current day. Below that, users can view various fishery load and energy supply information. The energy supply information includes the PV output and the battery availability. The fishery load mainly consists of the power consumption of the feeding machine, aerator, and recharge and drainage pump. Among these three types of loads, especially the latter two are greatly influenced by the environment. Therefore, real-time monitoring is necessary to detect any issues as early as possible.

For the aerator, temperature affects the oxygen transfer rate, and cloud cover affects photosynthesis, leading to fluctuations in the oxygen content in the water. Thus, it is necessary to adjust the amount of oxygen provided by the aerator to maintain an appropriate level of oxygen content.

As for the recharge and drainage pump, it is mainly used to maintain the water level in the fishponds. The water level in the ponds is influenced by factors such as atmospheric pressure, wind speed (which affects evaporation), precipitation, and soil structure (which affects infiltration). To meet the growth requirements of the fish, timely pumping and drainage using the recharge and drainage pump are needed. During this process, it is important to monitor whether the energy supply can meet the demand to ensure the system's safety. An alarm notification is set at the top of the interface, which turns red when the power cannot meet the load demand.

3.3. Weather forecasting subsystem

By clicking on the weather type icon at the top of the interface, users can enter the third interface, as shown in Figure 6. This interface displays various fishery meteorological parameters related to fish farming and fishery load, including surface wind speed, temperature, rainfall, and atmospheric pressure.

Clicking on the weather forecast option within the fisheries meteorological interface allows access to the weather forecasting subsystem, as illustrated in Figure 7. The implementation process is shown in Figure 8, it shows the training process and the internal processes of the two functions of get data and forecast in the APP. This system primarily serves two functions: data retrieval and forecasting. When entering the data retrieval function, you can choose between meteorological station data and PV station observation data. The former is obtained through an API provided by a weather data service provider, while the latter relies on historical records from complementary meteorological observation facilities installed at PV stations. The system provides interfaces for users to submit observation records over the network. It also offers a file-based data submission option, allowing offline forecasting when the file format requirements are met. Clicking on the forecasting option leads to a forecasting type selection interface, where you can choose between temperature and solar radiation. After making your selection, you will receive the forecasted results.

This system uses the LSTM model to predict the influential meteorological factors on PV energy in the fishing industry, mainly including temperature and solar radiation. LSTM is a deep learning model first proposed by Hochreiter and Schmidhuber [26]. Figure 9 shows the structure of the LSTM model. In this system, a single-

Figure 5
APP diagram of the power system part of the fishery system

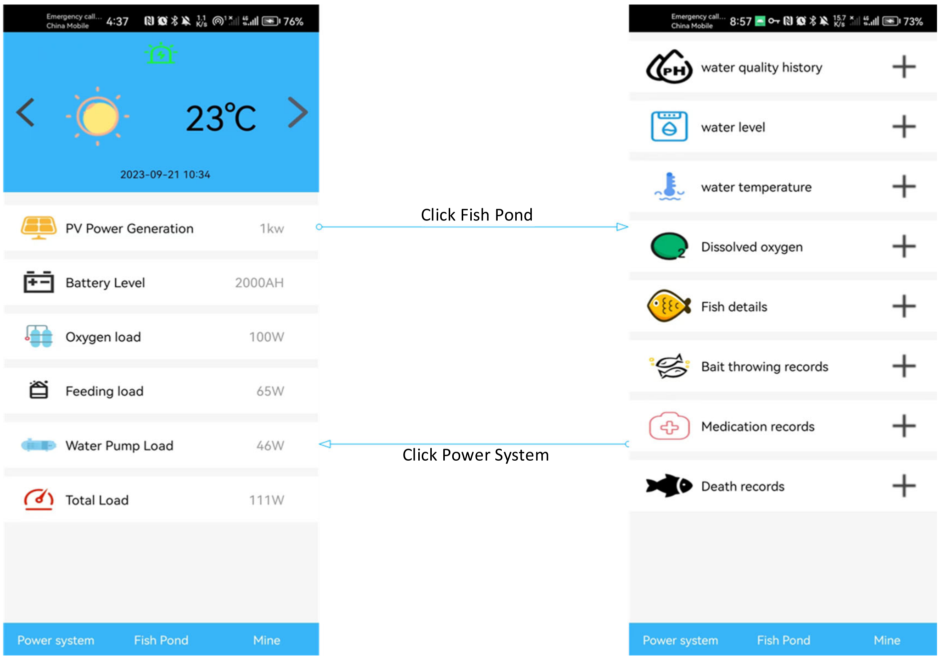
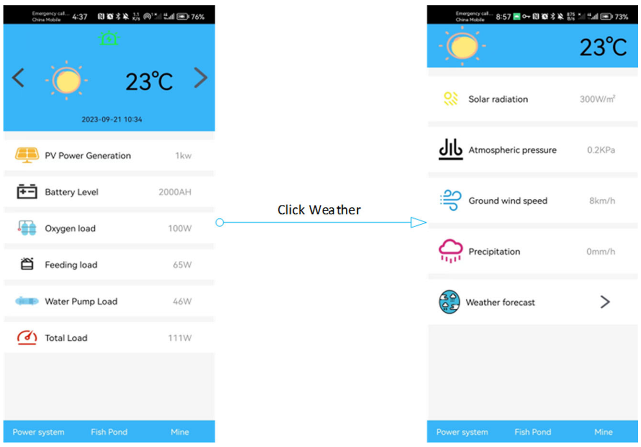


Figure 6
APP diagram of the fishery weather part of the fishery system



layer LSTM with 32 units and 5400 parameters is used. The input data consist of historical meteorological data and relevant weather data, while the output data are the solar radiation or temperature for the next 24 h. Two models are trained on the data from PV stations and meteorological stations and deployed on the Android platform. Figure 10 illustrates the data preprocessing process.

4. Experimental Results

During the course of the study, the performance of the LSTM model was tested. The model was built and trained using Python 3.7 and the TensorFlow 2.11 framework. Due to the small model size, it was sufficient to use an NVIDIA GeForce MX250 for computation.

The training data used for this study were Beijing meteorological station observation data provided by the data service provider WheatA, as shown in Figure 11. Table 3 describes the input data, which includes either solar radiation or temperature, along with other meteorological parameters such as cloud cover, wind speed, and air humidity. Table 4 outlines the dataset division. The training set and

Figure 7
APP demo diagram of the meteorological subsystem

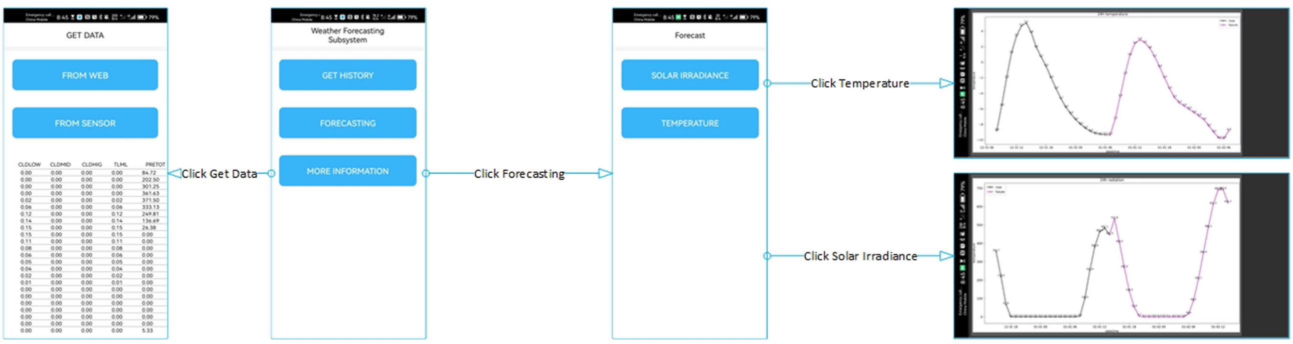


Figure 8
Flow chart of the meteorological subsystem

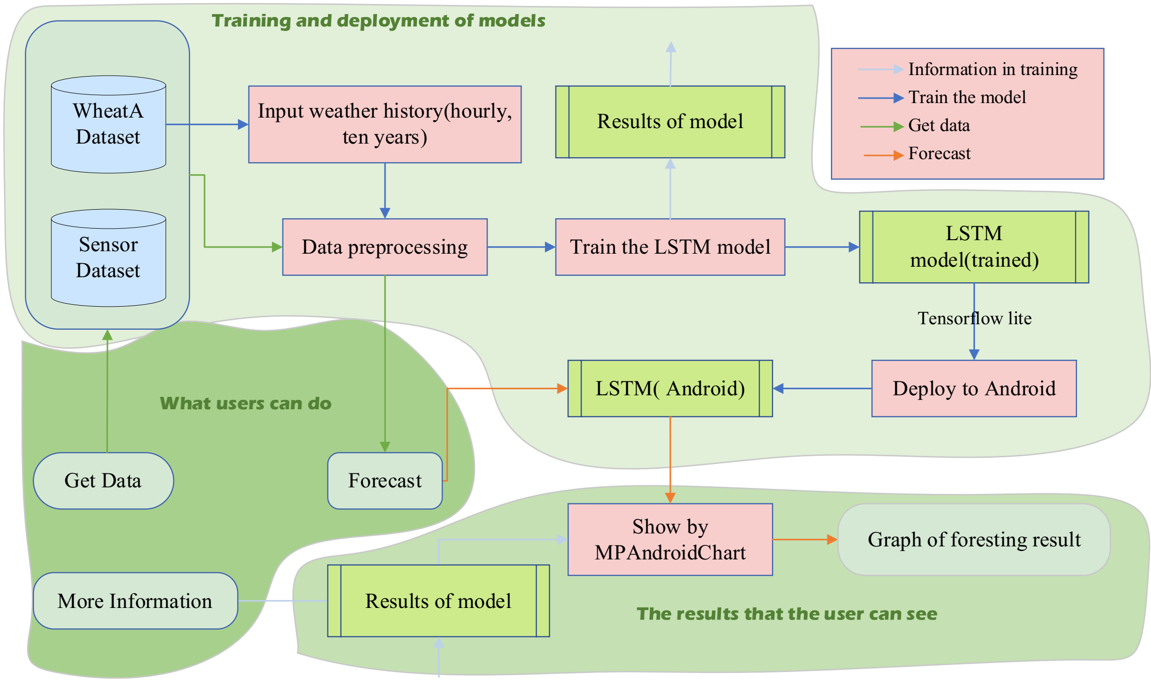


Figure 9
Architecture diagram of LSTM

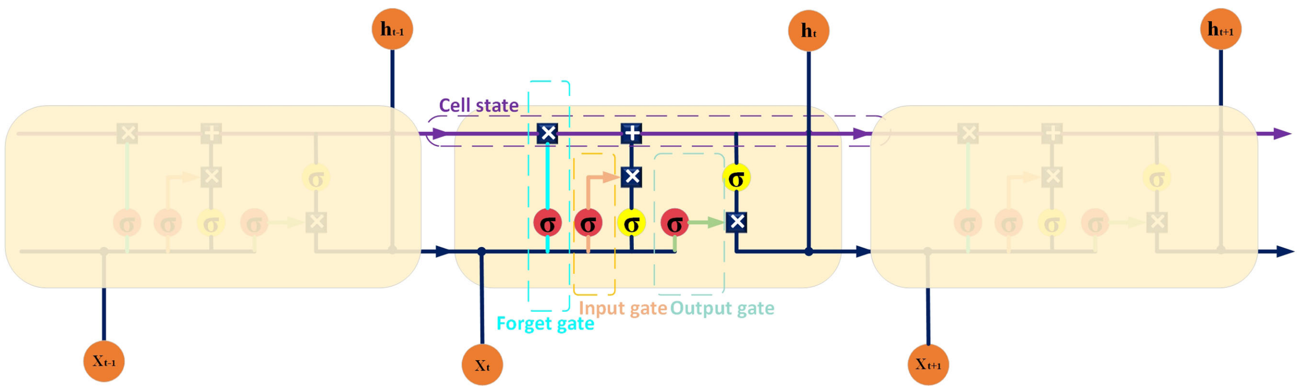


Table 3
Dataset information

Parameters	Unit	Description
Air temperature	°C	Air temperature measured 2 m above the ground
Precipitation	mm/hour	Total bias-corrected precipitation, over land only
Snowfall	mm/hour	The amount of snowfall within the land area
Snow mass	kg/m^2	Only snowfall over land areas is included
Air density	kg/m^2	Air density at ground level
Top of atmosphere solar radiation	W/m^2	Incident shortwave radiation flux at the top of the atmosphere
Ground-level solar radiation	W/m^2	Surface shortwave radiation flux
Cloud cover		The percentage of cloud cover obtained by summing all heights above the ground

Figure 10
Flow chart of data processing

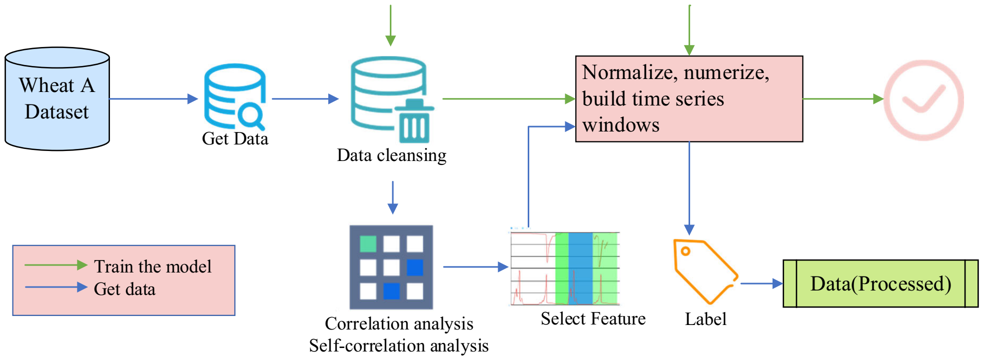


Table 4
Training set, validation set, and testing set

Set	Number	Percentage
Training set	70128	80
Validation set	8760	10
Testing set	8760	10

Table 5
Comparison of five models on the WheatA dataset

Model	MAE	RMSE
ResNet (solar radiation)	73.54	123.8
RNN (solar radiation)	56.46	96.38
iTransformer (solar radiation)	48.40	98.56
LSTM (solar radiation)	37.60	69.47
ResNet (temperature)	10.97	12.59
RNN (temperature)	2.16	2.85
iTransformer (temperature)	1.73	2.55
LSTM (temperature)	1.58	2.09

validation set were employed for model training and monitoring potential overfitting or underfitting throughout the training, whereas the test set was utilized to evaluate the model's ultimate performance. Table 5 shows the mean absolute error (MAE) and RMSE of four models, including ResNet [27], RNN [28], LSTM, and iTransformer [29], in predicting temperature and solar radiation in the next 24 h, among which the LSTM model used in this paper has the best performance.

The measurement metrics used for evaluating the model results were MAE and RMSE. MAE reflects the model's actual error, while RMSE amplifies the impact of larger errors. Both metrics ensure that the units of measurement remain unchanged. After the model training converged, the MAE for temperature forecasting was 1.58 °C, and for solar radiation, it was 37.6 W/m². The RMSE for temperature forecasting was 2.09 °C, and for solar radiation, it was 81.47 W/m². Figure 12 displays the training results for the 1st, 4th, and 24th hours, showing that the model can effectively predict future temperature and solar radiation.

Since TensorFlow Lite lightweighting the model, it is essential to understand the performance loss after compression. To assess this, tests were conducted on the test set. Two models were trained: one in TensorFlow (tf) format and the other in TensorFlow Lite (tflite) format. Taking temperature forecasting as an example, Table 6 presents a comparison of the two formats in various aspects. With a precision of one decimal place, the input mismatch rate between the two models was 1.92%. In terms of MAE, the tf format model was 1.58, while the tflite format model was 1.59, a difference of approximately 1%. Looking at the RMSE metric, the tf model was 2.09, while the tflite model was 2.11, again with a difference of about 1%. The performance was nearly identical, but in terms of memory usage, the tf format model was 794 KB, while the tflite format model was only 24 KB, a reduction of 1/33, indicating a significant compression effect on the model.

Table 6
Comparison between LSTM (TensorFlow) and LSTM (TensorFlow Lite)

Model	Storage	MAE	RMSE
LSTM (TensorFlow)	792 KB	1.58	2.09
LSTM (TensorFlow Lite)	24 KB	1.59	2.11

The experimental results mentioned above indicate that the model, after undergoing lightweight processing with TensorFlow Lite, reduced in size to 1/33 of its original size while still retaining 99% of its performance. This forms a solid foundation for deploying multiple models on the edge.

5. Discussion

In the context of contemporary fishery parks, we have developed a mobile application that integrates the consideration of fishery meteorology into the development of the aquaculture information system. This application not only offers general basic information services for aquaculture systems but also emphasizes meteorological information. Previously, the impact of meteorological factors on aquaculture systems was overlooked in the development of applications for monitoring aquaculture environments. For instance, the intelligent smartphone application developed by Lopez-Betancur et al. [30] and Siskandar et al. [31] effectively monitors real-time water quality parameters but fails to consider meteorological parameters. However, when data scientists provide solutions for fishery systems, they must consider meteorological information, which is closely associated with fishery systems, in addition to crucial information such as water quality parameters. Data derived from the same source are often more amenable to processing. Moreover, given that aquaculture-related devices are primarily employed to regulate the aquatic environment, their control and the

Figure 11
Map information of the meteorological station

Figure 12
Forecasting effect plot of the trained model (steps 1, 4, 24)

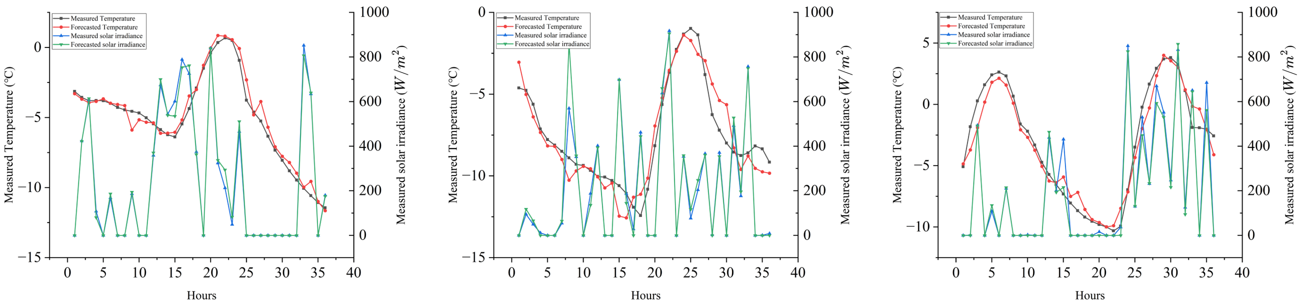


Table 7
Comparison between recent system and our system

Ref.	Water quality parameters	Instability of solar energy	Weather forecast	Meteorological parameters
Lopez-Betancur et al. [30]	√	×	×	×
Siskandar et al. [31]	√	×	×	×
Jamroen et al. [32]	√	√	×	×
Proposed	√	√	√	√

weather jointly influence the water environment. Recording meteorological factors also facilitates load analysis. In the investigation of PV energy supply, such as the research conducted by Jamroen et al. [32], although the instability of solar energy was taken into account and alternative energy sources were utilized to supplement insufficient solar power, it did not furnish managers with preemptive decision-making information. In contrast, our research accounts for the instability of PV power generation and provides 24-hour hourly forecasts of sunlight and temperature based on meteorological records, commencing from the principle of PV power generation. This enables improved electricity scheduling and estimation of the utilization of alternative energy sources for the subsequent day. Additionally, we have created a data upload interface to fulfill the requirements of model training using local meteorological information obtained from PV stations. Table 7 illustrates the above comparisons.

By taking into account the various influences on modern fishery parks from the standpoint of fishery meteorology, the app developed in this study is capable of accommodating the production demands of future modern fishery parks and holds significant potential for future applications. Furthermore, it is evident that such diverse data requirements necessitate not only support from terminal devices but also ongoing enhancements in other aspects of Internet of Things technology within modern fishery parks.

6. Conclusion

As modern fisheries continue to evolve, there is a growing need to consider a wide range of information within the fisheries system. This includes information related to aquaculture, fisheries load, and renewable energy supply, all of which are influenced by fisheries meteorology. Based on research and surveys conducted in the application market, it has been found that existing systems have not comprehensively addressed the above-mentioned information and failed to meet the demands of modern fisheries. Therefore, we have developed the Fisheries Meteorological Comprehensive Information Service System for modern fisheries parks. Specifically tailored to meet the requirements of modern fisheries, it includes features for renewable energy integration and forecasting. To meet the demands of modern fisheries for renewable energy and forecasting, we deployed an LSTM model at the edge using TensorFlow Lite. This system supports inputs from both PV stations and meteorological stations, ensuring stable access to forecast information. In order to validate the performance of LSTM at the edge, we deployed the model on Android using TensorFlow Lite. Through experimental comparisons, we found that the tflite format of the model reduced in size to 1/33 of the original while retaining 99% of the performance of the tflite format model. This allows us to meet the requirement of deploying multiple models at the edge while also providing effective information for PV energy forecasting.

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Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Supportive Materials

Code in this article can be obtained from https://gitee.com/XL-Zhao/fishery-weather

Conflicts of Interest

Xueqian Fu is an Editorial Board Member for Artificial Intelligence and Applications, and was not involved in the editorial review or the decision to publish this article. The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

The data that support the findings of this study are openly available in WF_DATA at http://doi.org/10.5281/zenodo.10575481

Author Contribution Statement

Xiaolong Zhao: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Xueqian Fu:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Supervision, Project administration, Funding acquisition. **Xiangrong Zeng:** Methodology, Software, Investigation, Resources, Data curation, Writing – original draft. **Ningyi Zhang:** Methodology, Software, Investigation, Resources, Data curation, Writing – original draft.

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