Smart Irrigation System with Predictive Analytics using Machine Learning and IoT

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Abstract

Water scarcity is a significant issue in agriculture, making efficient irrigation practices crucial for sustainable farming. Integration of Internet of Things (IoT) and machine learning technologies are becoming of great importance to improve irrigation efficiency and reduce water usage. In this paper, we propose an intelligent irrigation system that take the advantage of IoT to improve the predictive analytics of groundwater levels. Our system used a deep learning to estimate the groundwater level using convolutional recurrent model that analyzed the sensory measurements necessary to predict groundwater levels. The model is trained on a large dataset of time series records and corresponding groundwater levels, allowing it to learn the complex patterns and relationships between time series features and groundwater levels. The experimental predictive analytics provided accurate irrigation recommendations, and the remote monitoring capabilities allowed farmers to adjust the irrigation schedule as needed.

Keywords: Smart Irrigation System; Intelligent systems; Predictive Analytics; Deep Learning

1. Introduction

A smart irrigation system is a modern, innovative solution that uses advanced technology to provide optimized and efficient irrigation for crops and gardens. This system utilizes various sensors, weather data, and moisture meters to monitor the soil and plant requirements and automatically adjusts the watering schedules to ensure optimal growth conditions. By using this technology, farmers can reduce water usage, minimize water wastage, and reduce labor costs associated with manual irrigation. Smart irrigation systems can be operated remotely using mobile apps, and they provide real-time data and analytics to help farmers make informed decisions about their irrigation practices. Additionally, these systems can be customized to suit different crops, soils, and weather conditions, making them versatile and adaptable. Overall, a smart irrigation system is an excellent investment for any farmer or gardener who wants to improve their productivity, conserve resources, and increase yields.

Predictive analytics is an essential component of a smart irrigation system, as it allows the system to anticipate and respond to changing weather patterns, soil moisture levels, and plant growth requirements. Predictive analytics uses historical and real-time data to identify trends and patterns that can help predict future conditions. By analyzing this data, a smart irrigation system can optimize its watering schedules to ensure that plants receive the right amount of water at the right time, reducing water wastage and ensuring optimal plant growth. For example, a predictive analytics model can use data on weather patterns and forecasted precipitation to adjust irrigation schedules accordingly. If there is a high chance of rain in the coming days, the system can reduce the amount of water it applies to the plants, while if there is a prolonged dry spell, it can increase the watering frequency to prevent plants from experiencing drought stress.

Machine learning (ML) is an advanced technology used in predictive analytics to improve the accuracy of the smart irrigation system. With the help of ML algorithms, the system can learn from historical and real-time data and make predictions and decisions based on the analyzed data. One of the significant advantages of using ML algorithms in predictive analytics is that they can automatically adapt to changing conditions, making them more accurate and reliable over time. For example, if the weather patterns change or there is a new crop planted, the ML algorithm can quickly adjust and make the necessary changes to the irrigation schedule to ensure optimal plant growth. ML

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algorithms also allow for more precise irrigation practices by analyzing multiple factors, such as soil moisture, temperature, and humidity, to determine the exact amount of water required by the plants. This reduces the chances of under or overwatering, resulting in healthier and more productive plants. Furthermore, ML algorithms can detect anomalies and irregularities in the system, such as leaks or blockages, and alert the farmer to take immediate corrective actions. This helps in preventing water wastage and ensuring that the irrigation system is running efficiently.

This work contributes to the body knowledge as follows.

- This research develops an intelligent smart irrigation system that use deep learning to automatically analyze a wide range of data related to soil moisture, temperature, humidity, weather patterns, and plant growth requirements to optimize irrigation practices. Our system is trained on historical and real-time data, enabling it to identify patterns and trends that can help predict future conditions. Our system would be customizable to suit different crops, soils, and weather conditions, and it would be scalable to meet the needs of different farming operations.
- Our system is able to estimate the groundwater level using an improved deep learning model that process and analyze ground data from different locations.
- Experimental assessments on the public groundwater dataset demonstrated that our system can accurately forecast the groundwater level, which makes it a robust candidate for improving the functionality of smart irrigation system in real-world.

The sections of this paper are as follows: An overview of related studies is presented in section 2. The methodology of our system is presented in section 3. The experiments analysis is given in section 4. Our conclusions are derived in section 5.

2. Related Works

Smart irrigation and groundwater analysis are important areas of research in agriculture, as they have the potential to significantly improve water use efficiency and sustainability. There are several related works that focus on developing and implementing technologies to monitor and manage irrigation practices and groundwater resources. the paper [1] proposed a method for designing a precision agriculture system using a distributed computing architecture in an IoT context. It argued that system can benefit from the integration of IoT technologies and propose a system architecture that used distributed computing to process data collected from sensors, cameras, and other IoT devices. The paper [2] presented a system for optimizing energy consumption and irrigation in tunnel farming using IoT technologies in a way that enable tunnel farming to benefit from the integration of IoT to improve resource management and reduce costs. The system consisted of several elements, involving sensors for monitoring environmental situations, actuators for regulating irrigation and energy handling, and a central server for data processing and analysis. It used machine learning algorithms to analyze data collected from the sensors and make decisions about when and how much water and energy to use for irrigation and climate control. The paper [3] proposed a smart agricultural machine that uses computer vision-based weeding and variable-rate irrigation to optimize crop yield and reduce labor costs. It demonstrated that traditional farming methods can be inefficient and time-consuming, and that the integration of ML and IoT technologies can improve the accuracy and efficiency of farming operations. It used cameras for detecting and classifying weeds, actuators for dispensing herbicide, and a variable-rate irrigation system for optimizing water usage. The paper [4] discussed the implementation of an IoT platform for smart farming and provides insights and lessons learned from the implementation process. The sensors was used to monitor environmental conditions, actuators for controlling irrigation and fertilization, and a central server for data processing and analysis. It described the design and implementation of the platform and provide insights into the challenges encountered during the implementation process, such as connectivity issues, data management, and system integration. The paper [5] highlighted the potential benefits of using IoT technologies in hydroponic farming and provided a practical example of how such technologies could be used to optimize resource management and improve crop yield. This system could be used as a model for other hydroponic farming operations seeking to improve their efficiency and sustainability. The paper [6] proposed a model for predicting the water demand of mixed crop fields and a smart irrigation system that uses this information to optimize irrigation scheduling. It argued that traditional irrigation methods are often inefficient and can result in over-watering or under-watering of crops, which can reduce crop yield and increase water usage. The paper [7] examined the adoption of small-scale irrigation farming as a climate-smart agriculture practice and its influence on households in rural areas. It also discussed that small-scale irrigation could help farmers adapt to the effects of climate change and improve their resilience to weather-related shocks. The paper [8] proposed a precision irrigation system (PIS) that used a sensor network technology to optimize irrigation scheduling and improved water use efficiency. The

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authors argued that traditional irrigation methods are often inefficient and can result in over-watering or under-watering of crops, which can reduce crop yield and increase water usage. The proposed PIS consisted of soil moisture sensors, weather sensors, and an automated irrigation controller that uses real-time data from the sensors to optimize irrigation scheduling. The paper [9] proposed an iPathology system that used a combination of robotic imaging and machine learning algorithms to identify and classify plant diseases. The system consisted of a robotic arm that is equipped with a high-resolution camera and a ML algorithm that is trained to recognize disease symptoms. The paper [10] proposed an automated steering system that used automated steering to guide the tractor during planting and digging, reducing the amount of soil disturbance and improving the accuracy of the process. The system can help peanut farmers to increase their profitability and reduce their environmental impact. The paper [11] proposed a system that integrates wireless sensor networks (WSNs) and multi-agent systems (MAS) to monitor and manage crop irrigation. This system was applied to combine measure soil moisture levels, weather conditions, and other environmental factors, that are transmitted wirelessly to a central control system, which uses MAS to analyze the data and determine appropriate irrigation schedules.

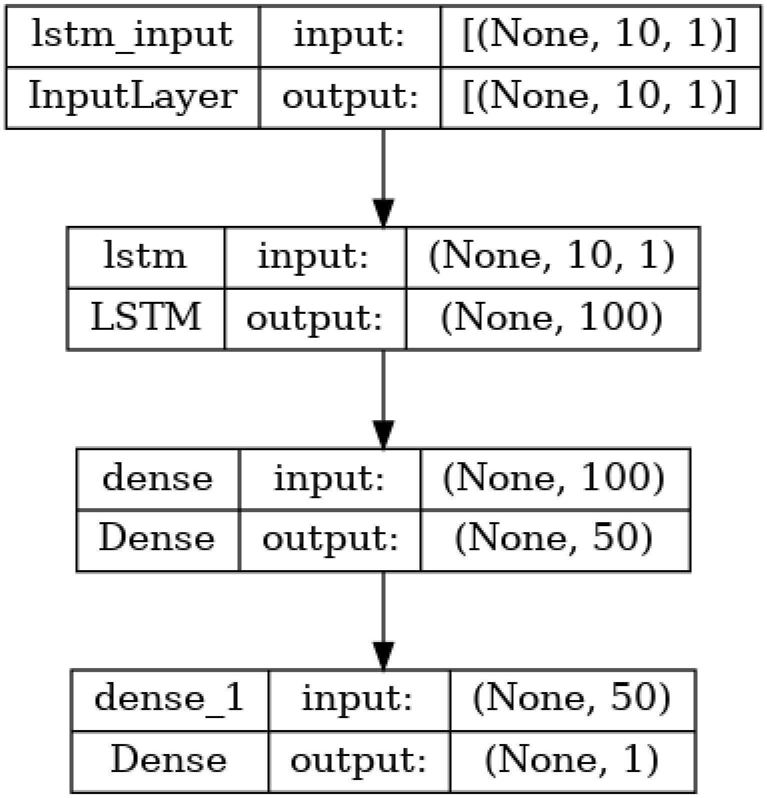

Figure 1: Architecture of our model.

3. Methodology of our Intelligent System

In our system, we use Long Short-Term Memory (LSTM) as a popular technique for time series forecasting, hence it is applied to groundwater level estimation. The LSTM model is a type of ML that can capture long-term dependencies in the input sequence, making it suitable for predicting groundwater levels, which are affected by both short-term and long-term factors. The LSTM model has been widely used in hydrological studies to estimate groundwater levels based on various input features, such as rainfall, temperature, and soil moisture. One advantage of LSTM models for groundwater level estimation is their ability to handle non-linear relationships between the input features and groundwater level output. The LSTM model can capture the temporal patterns and dependencies in the input features, which are critical for groundwater level estimation (see Figure 1). Additionally, LSTM models can handle missing data and can effectively learn from time series data with irregular intervals. These properties make LSTM models a promising tool for groundwater level estimation, which is a complex and challenging task due to the influence of

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various factors such as climate change, human activities, and geological conditions. the computation of the LSTM is formulated as follows:

$$i_t = \sigma(W_i([x_t, y_{t-1}])) \tag{1}$$
$$f_t = \sigma(W_f([x_t, y_{t-1}])) \tag{2}$$
$$o_t = \sigma(W_o([x_t, y_{t-1}])) \tag{3}$$
$$g_t = tanh(W_g([x_t, y_{t-1}])) \tag{4}$$
$$c_t = f \odot c_{t-1} + i \odot g \tag{5}$$
$$y_t = o \odot tanh(c_t) \tag{6}$$

In the above formulation, the i_t, f_t, o_t denote the input, forget, and update gate. The output of our model is assessed during the training with log-cosh loss, which is used to update the training parameters. It is defined as follows:

$$\text{Logcosh:} \; l = \frac{1}{n}\sum_{i=1}^{n} log(\cosh(Y_i - \hat{Y}_i))^2 \tag{7}$$

with $Y_i$and$\hat{Y}_i$ denote the actual groundwater level and predicted one, correspondingly.

4. Results and Discussions

To experiment the proposed system, we use continuous time-series data denoting as continuous groundwater level measurements recorded by Department of Water Resources over interval with length from 15 m to 1 hour [16]. Some records are belonging to the California Data Exchange Center. The data records were captured from different locations including Butte, Colusa, Glenn, Mendocino, Modoc, Sacramento, San Joaquin, Shasta, Siskiyou, Solano, Sutter, Tehama, Yolo, and Yuba Counties. Variations in groundwater levels and mobility in a basin, and how these are impacted by different aspects of release and recharge, can primarily be learned from water-level measurements. The datasets consisting of around million of samples each composed of 12 variables needed to estimate groundwater. The data was collected from 3/25/1992 to 12/27/2018, at both daily and monthly basis. The exploratory statistics of our datasets are given in Table 1.

Table 1: Summary statistics of the groundwater level dataset.

	COUNT	MEAN	STD	MIN	25%	50%	75%	MAX
WLM_RPE	1042002	49.911	49.082	-0.570	26.450	36.692	68.210	522.650
WLM_RPE_QC	1048575	12.423	30.961	1.000	1.000	1.000	2.000	255.000
WLM_GSE	1039724	48.130	48.994	-3.170	25.000	35.546	65.700	520.000
WLM_GSE_QC	1048575	12.175	31.354	1.000	1.000	1.000	1.000	255.000
RPE_WSE	963223	21.899	19.311	-12.492	9.922	16.798	27.683	187.804
RPE_WSE_QC	1048575	22.149	68.051	1.000	1.000	1.000	1.000	255.000
GSE_WSE	954445	20.253	19.477	-15.292	8.360	15.187	26.195	186.534
GSE_WSE_QC	1048575	32.770	71.575	1.000	1.000	1.000	2.000	255.000
WSE	956650	27.523	49.853	-170.798	2.888	19.063	48.565	514.804
WSE_QC	1048575	32.397	71.405	1.000	1.000	1.000	2.000	255.000

A correlation map for groundwater data is visualized in Figure 2 to illustrates the strength and direction of the linear relationship between different variables in a groundwater dataset. This map is created by computing the correlation coefficients between all pairs of variables in the dataset and displaying the results as a color-coded matrix. Correlation coefficients measure the extent to which two variables are related and range from -1 (perfect negative correlation) to 1 (perfect positive correlation), with 0 indicating no correlation. By analyzing the correlation map, hydrologists and other water management professionals can gain insights into the complex interactions between different variables in a groundwater system and make more informed decisions about how to manage this critical resource.

More, the learning behavior of the proposed system can be observed in Figure 3. As shown, the model is able to consistently train on groundwater data. Plotting the prediction vs actual values is a common method used in evaluating the performance of a machine learning model. It involves comparing the predicted values generated by our model with the actual values to assess how well our model can make accurate predictions. The plot typically shows the predicted

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values on the x-axis and the actual values on the y-axis, with each data point representing an observation in the dataset. Our model's predictions are plotted on daily basis against actual values, as shown in Figure 4.

	WLM_GSE	WLM_GSE_QC	RPE_WSE	RPE_WSE_QC	GSE_WSE	WSE	target
WLM_GSE	1.000000	1.000000	-0.146004	-0.331186	-0.118776	0.146004	-0.117612
WLM_GSE_QC	1.000000	1.000000	-0.146004	-0.331186	-0.118776	0.146004	-0.117612
RPE_WSE	-0.146004	-0.146004	1.000000	-0.024217	0.999623	-1.000000	0.997602
RPE_WSE_QC	-0.331186	-0.331186	-0.024217	1.000000	-0.033501	0.024217	-0.032582
GSE_WSE	-0.118776	-0.118776	0.999623	-0.033501	1.000000	-0.999623	0.998004
WSE	0.146004	0.146004	-1.000000	0.024217	-0.999623	1.000000	-0.997602
target	-0.117612	-0.117612	0.997602	-0.032582	0.998004	-0.997602	1.000000

Figure 3: Illustration of the correlation map of the dataset variables.

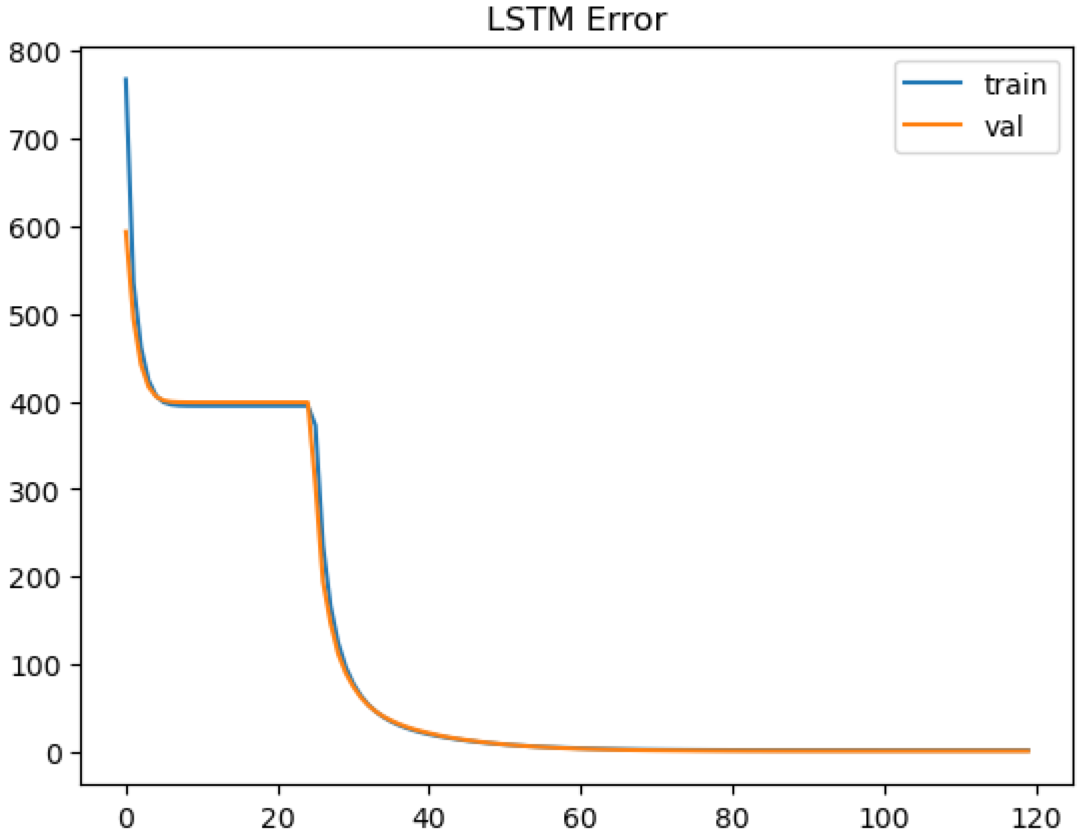

Figure 2: the learning curves of the proposed system

5. Conclusion

This research, we develop a smart irrigation system that integrate intelligent statistical models and machine learning algorithms to predict groundwater levels with high accuracy and precision. These predictions can be used to develop early warning systems for droughts, floods, and other water-related disasters, as well as to optimize groundwater extraction rates and recharge strategies. By predicting groundwater levels, we can make more informed decisions about how to allocate water resources and ensure sustainable water use. With the growing recognition of the

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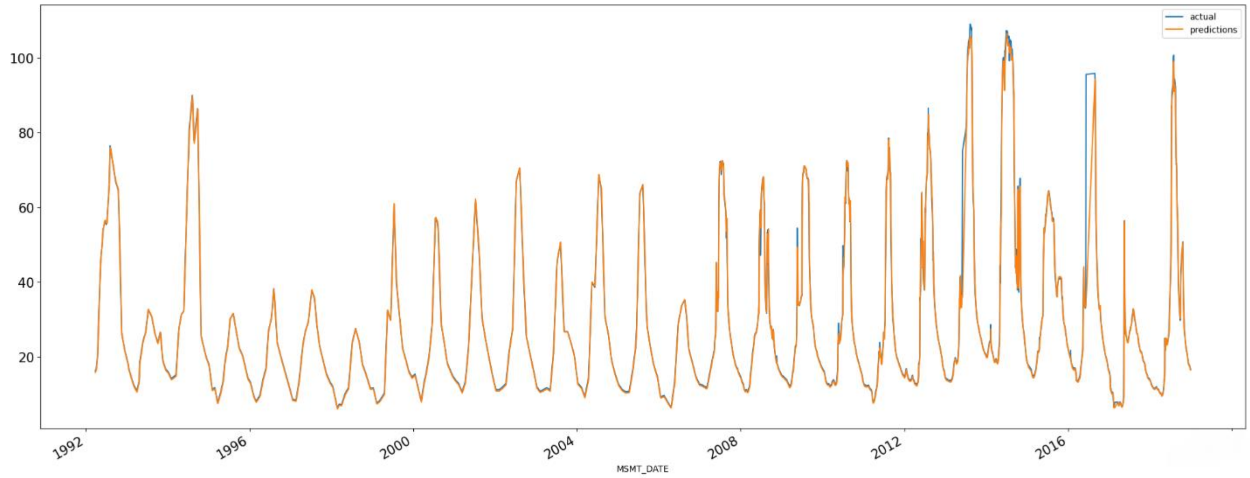

Figure 4: the prediction plot of our system

importance of groundwater management, there is a need for continued investment in research and development to improve our understanding of smart irrigation system and enhance our ability to predict and manage groundwater resources effectively.

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