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Sustainable and precision agriculture biotechnological model using deep learning algorithm

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Abstract

Objective

With the help of weather data from the agricultural Internet of Things (IoT) method's, it is possible to plan for changes in the weather. This is an excellent way to prepare and keep track of the production of green agriculture. Thus, the aim of this study was to make weather information forecasting more accurate in the Precision Agriculture (PA) system.

Materials and methods

It is difficult to accurately predict future trends as the data is complicated and requires simple linear links. The evolution of communication technology and the increasing number of interconnected things have had a profound impact on the agricultural sector. Advances in AI, and deep learning in particular, have facilitated faster and more accurate data processing in this modern digital era. A new data analytics technology called deep learning has the potential to make farming more efficient, eco-friendly, and predictable. In this study Deep Learning (DL) predictions with a two-level decomposition structure and Biotechnology (BT) were used to make the prediction of weather information in the Precision Agriculture (PA) system more accurate. First, the weather data was decomposed into four parts. Then, the Gated Recurrent Unit (GRU) systems were created as sub-predictors for each part.

Results

First, the weather data was decomposed into four parts. Then, the Gated Recurrent Unit (GRU) systems were created as sub-predictors for each part. The predictions for the medium and long-term future were made by combining the results from the GRUs. Using weather data from the BT-based IoT systems, it was confirmed that the tests work with the suggested structure.

Conclusions

The proposed prediction method can predict the temperature and humidity correctly and meets the PA standards. It can assist farmers in the management of their agricultural operations. It is possible to provide an initial prediction and assessment of extreme weather conditions in agriculture to minimize risks and maximize profits.

Keywords: Biotechnology, deep learning, precision agriculture, sustainability

Paper Type: Research Paper.

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Introduction

Agriculture is critical to the economies of emerging markets, providing a wide range of food, cash, and employment opportunities for people in rural areas. For many years, agriculture has been growing and preparing essential foods. Agricultural production protects the forests, the food produced from milk and the fruit trees (Jung et al. 2021). In addition to the production of food and other products, agriculture is sometimes the backbone of many countries because it creates many jobs. Growing fruit is an essential and rewarding part of agriculture. Fruit safety and the amount of fruit produced per person are now considered as critical signs of a country's economic growth and standard of living. Fruit growing has many financial benefits, such as earning money, preventing soil pollution, improving air quality and boosting the labour market (Angin et al. 2020).

Internet of Things (IoT) advancements let devices collect data, making many intelligent systems much brighter (Boursianis et al. 2022). The precise agricultural system has been a critical IoT system in recent years. It uses new technologies to increase production, make more money and produce things of higher quality. Precision agriculture (PA) is very promising and has a great impact on food production, by making it safe and reliable (Cisternas et al. 2020). An important area of investigation into IoT systems for PA is creating a customized environment that works best by adapting to the weather in terms of temperature and humidity (Yin et al. 2021). This means making optimal use of resources such as energy, space and labour to make output more efficient. It can be difficult to predict the weather based on sensor data because the data contains a lot of complicated, non-linear relationships and different parts (Zoran et al. 2022). The IoT device has collected and stored a lot of data with biotechnology (BT) because it has a high sampling rate (Nabeesab Mamdapur et al. 2019). This allows the researcher to look at sensory data, find new features and guess what will be new in the future (Barron et al. 2020).

They are several to solve the problem of predictions based on time series data collected from IoT device monitors (Devi et al. 2024). Autoregressive Incorporated Moving Average (ARIMA) (López Rivero et al. 2020), Deep Neural Networks (DNN) (Saleem et al. 2023), Support Vector Machines (SVMs) (Sumarudin et al. 2021), and Echoing State Networks (ESN) with particle swarming optimizer (PSO) (Zheng & Li 2023) are some of the methods that have been used to look at and predict information about future time sequences (Surendar et al. 2024). However, these models cannot make accurate predictions when it comes to a natural BT-based IoT system because their data is too complicated and cannot simulate the nonlinearity well enough.

Deep Learning (DL) algorithms have recently shown that they are very good at capturing the features of complicated nonlinear data. Convolutional Neural Networks (CNN) (Sarma et al. 2022; Camgözlü & Kutlu 2023) and Recurrent Neural Networks (RNN) (Devi et al. 2024), as well as their improved forms such as Long Short-Term Memory (LSTM) (Gao et al. 2021), Gated Recurring Unit (GRU) (Akilan & Baalamurugan 2024), and Bidirectional LSTM (Bi-LSTM) (Peeriga et al. 2024) were used to extract features from temporally consecutive data. Bi-LSTM, an advanced version of LSTM, improves its efficiency by using temporally consecutive information in both directions (Choi & Zhang 2022). Despite an increase in the number of variables and the need to train over several generations, the Bi-LSTM model can consider a more complete input range. Moreover, data generation in agriculture and biotechnology has greatly increased in recent years due to the very rapid development of high-performance technologies (Mohammadabadi et al. 2024). These data are obtained from studying products, foods, and biological molecules to understand the role of different aspects of agriculture in determining the structure, function, and dynamics of living systems (Pour Hamidi et al. 2017). Artificial neural networks have been proposed to alleviate limitation of traditional methods and can be used to handle nonlinear and complex data, even when the data is imprecise and noisy (Pour Hamidi et al. 2017). Agricultural data can be too large and complex to handle through visual analysis or statistical correlations. This has encouraged the use of machine intelligence or artificial intelligence (Ghotbaldini et al. 2019). Thus, the aim of this study was to make weather information forecasting more accurate in the Precision Agriculture (PA) system.

Materials and methods

Proposed DL-based PA model with BT: Based on the forthcoming weather data, farmers can modify their planting and harvesting schedule, effectively utilize the benefits of local supplies, and ensure the long-term viability of the growing industry. Figure 1 depicts the IoT technology explicitly designed for PA. The BT-based IoT system consists primarily of five components: sensors, a displaying board, a computing device, a controller, and an agricultural actuator. Due to the outdoor nature of the establishment, the research implemented a BT-based IoT system that utilizes a battery-powered wireless sensor to gather temperature and moisture information. This data is then communicated to a computing facility, essentially a computer, for storage.

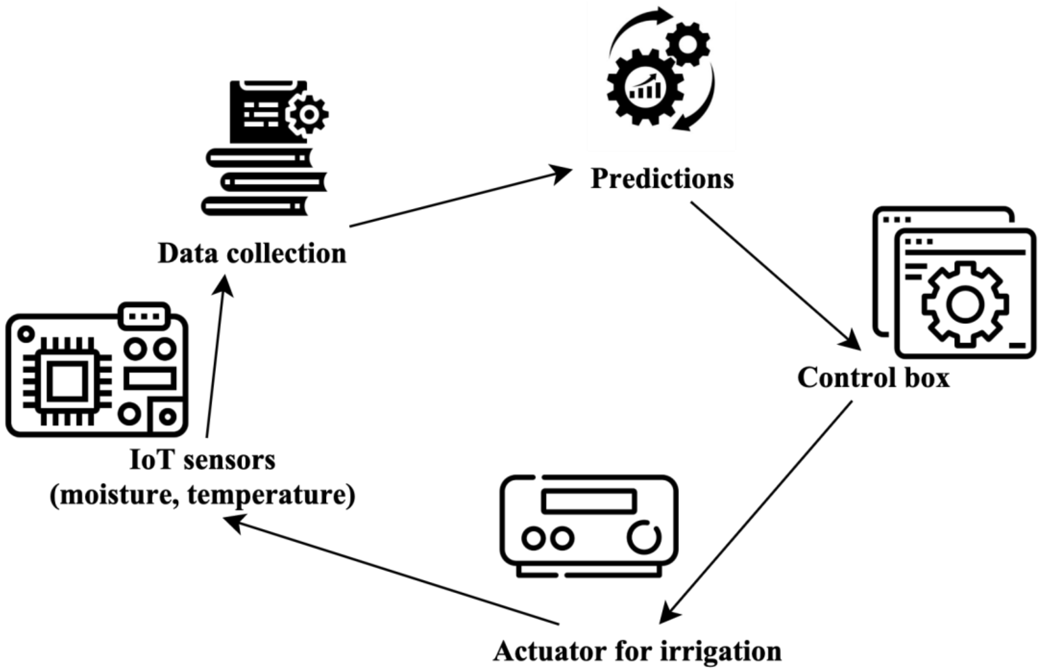

Figure 1. The architecture of the proposed DL-based PA model with BT

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A substantial amount of stored information was utilized to train the DL system to provide precise forecasts of future moisture and temperature. The primary function of the display screen was to exhibit the prevailing atmospheric conditions. The control unit was employed to regulate the irrigation actuators. The forecast findings must contain a two-term forecast according to the specific demands of the application. (1) Mid-term forecast: Offering precise forecasts of the climate and humidity for the upcoming 24 hours. (2) Long-term forecast: Delivering a mean daily temperature and moisture for 30 days. The former is utilized to direct the irrigation strategy for the following day, ensuring the efficient utilization of the water supply in BT-based IoT systems. The real-time watering timing and irrigation quantity are adjusted dynamically according to precise moisture and temperature estimates for the following 24 hours.

Model design: The model consists of three components: deconstruction, forecasting, and integration. Figure 2 displays the forecasting model for PA.

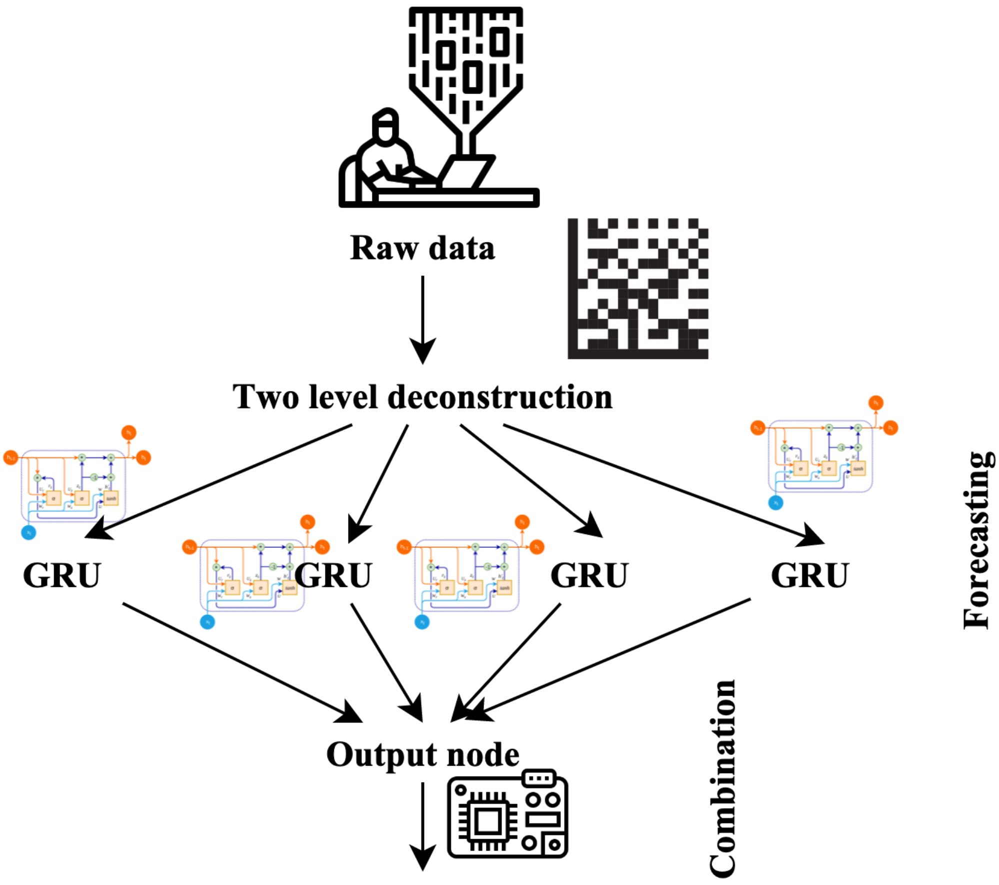

Figure 2. Forecasting model for the PA

The research employed a two-level deconstruction technique, breaking the initial information into four distinct components. Each element underwent a unique treatment to derive distinct GRU sub-predictors throughout the network learning phase. During the forecasting phase, distinct GRUs were employed to forecast the various components individually. The forecasts were aggregated to provide the ultimate projected outcomes in the resultant node for BT-based IoT systems.

Two-level deconstruction: A progressive two-level decomposition was employed to break down the original time series data. A decomposition cycle of 24 hours was used to obtain the pattern, daily period, and residue. Due to regularity in the residual generated from the initial decomposition, the research employed a second-level deconstruction to break down the residue into three more elements.

Figure 3 provides a detailed two-level deconstruction model for forecasting. The meteorological data, including moisture and temperature, underwent a first-level deconstruction. This resulted in the identification of three components: the trend, the daily phase, and the remainder. The remainder was further broken down, leading to the identification of the pattern, the yearly time, and the remainder.

Results and discussions

Experimental setup: The training information consisted of hourly humidity and temperature measurements, totaling approximately 35k documents collected between 2018 and 2023. The experiments used a 75:25 training set for evaluation. The experimental hardware and software settings were configured to run the proposed prediction algorithm for BT-based IoT systems. All learning algorithms were created using the Keras DL package, which is based on TensorFlow and is freely available. The studies were conducted on a personal computer with an Intel CPU i7 processor with 60 GHz and 6 GB RAM. To effectively describe the DNN, a significant number of hyperparameters must be configured. In the tests, the standard Keras' default variables were used to initialize the DNN, namely weight propagation. The research used the hyperbolic tangent as the activation value and the Rectified Linear Unit (ReLU) as the activation function for the GRU framework.

Prediction results: Figure 4(a) displays the extended forecast for temperature, including temperature information, mean daily temperature, and estimates for the next 30 days for BT-based IoT systems. It is evident that the projections closely align with the mean everyday temperature during the initial days. However, on the 12th day, the forecast falls below the mean, and on the 16th and 21st days, the forecast exceeds the mean. Based on the analysis, long-term predictions can provide a general understanding of future trends. However, due to the significant influence of uncertain elements on foreseeable weather conditions, correctly forecasting the impact of warm

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and cold air flows is not feasible. Figure 4(b) illustrates commonalities in humidity forecast for BT-based IoT systems.

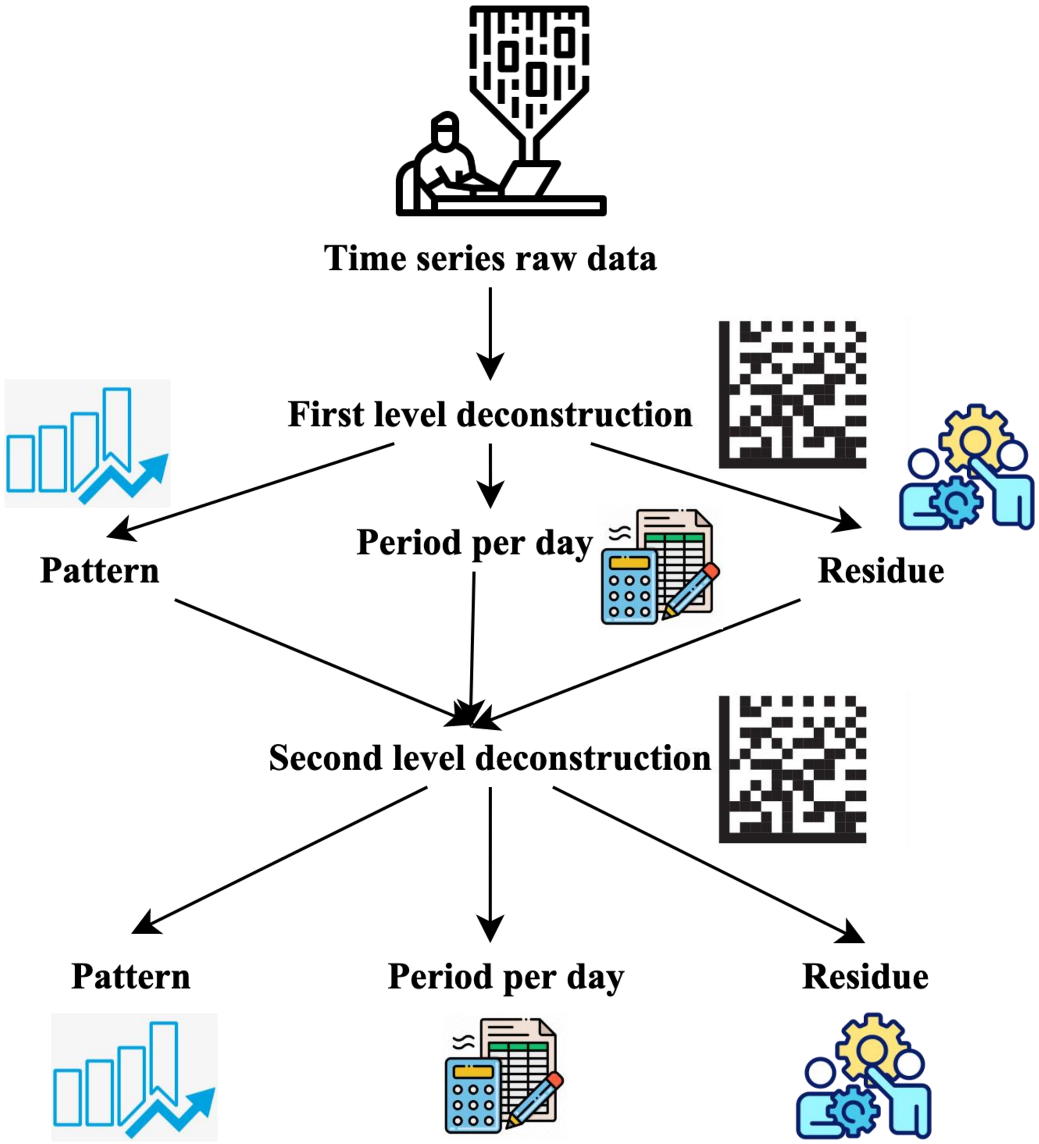
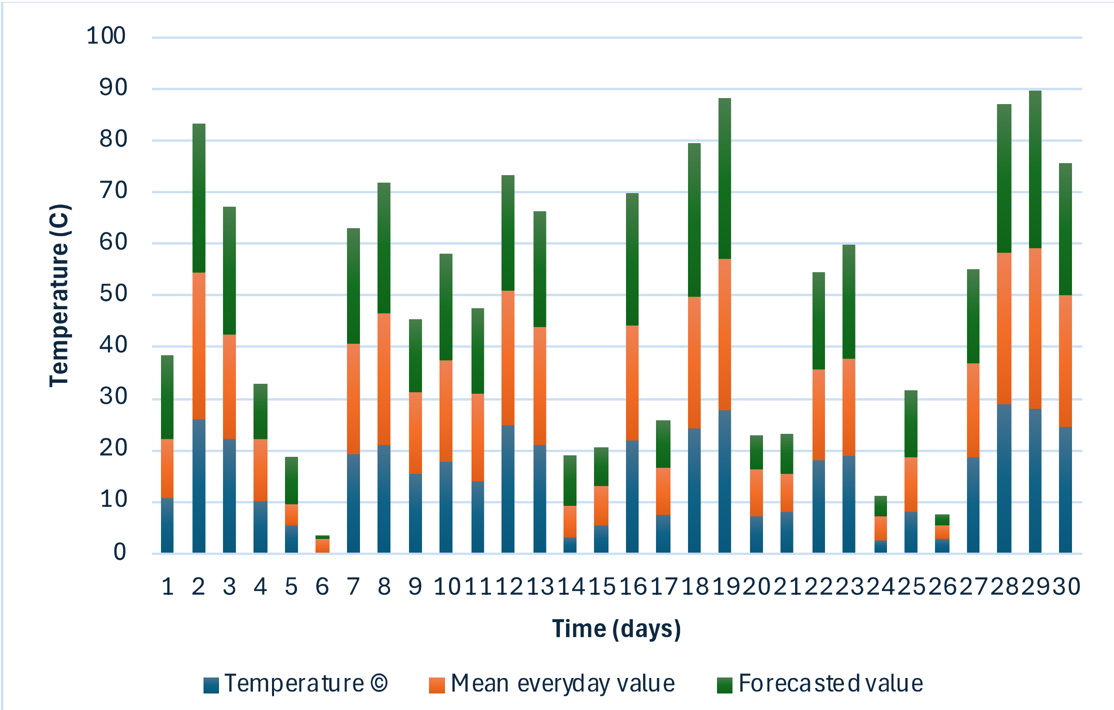
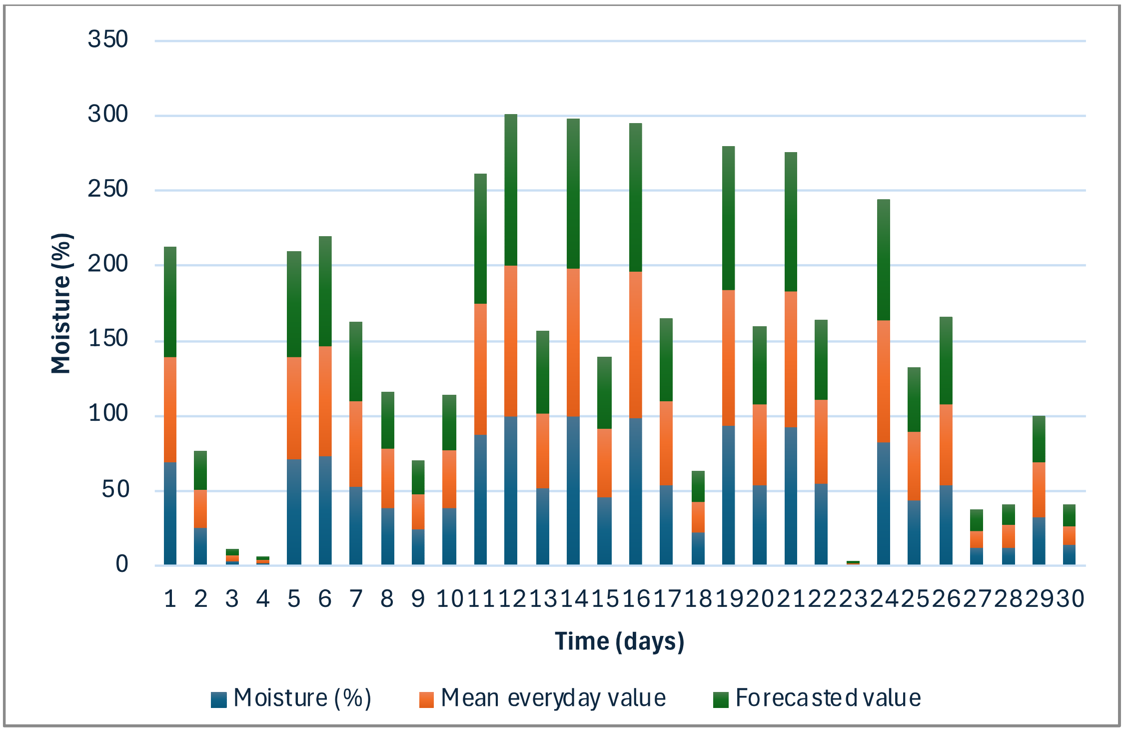


Figure 3. Two-level deconstruction model for forecasting



(a)



(b)

Figure 4. Temperature forecasting results (a) and moisture forecasting results (b)

Forecasting Comparison with other models: This experiment involved comparing the suggested approach with eight different methods and the deconstruction techniques known as seasonal-trend deconstruction techniques based on losses as the sub-predictors.

The temperature and humidity information are utilized to display the forecast outcome. Figure 5 compares the projected outcomes of several models, including RNN, LSTM, GRU, CNN, ANN, SVM, and the proposed model regarding Root Mean Square Error (RMSE). The study of forecasting outcomes demonstrates that deconstructed models exhibit superior performance compared to undecomposed ones. The suggested model demonstrates even more precise forecasting than the other approaches. The proposed model has a forecast RMSE for temperatures roughly 23.2% lower than the GRU and CNN methods. The suggested approach has an estimated RMSE for moisture around 9.8% smaller than the GRU and CNN methods. The findings demonstrate that the proposed technique is highly efficient, substantially reducing RMSEs. The GRU model proves to be the optimal option as the sub-predictor.

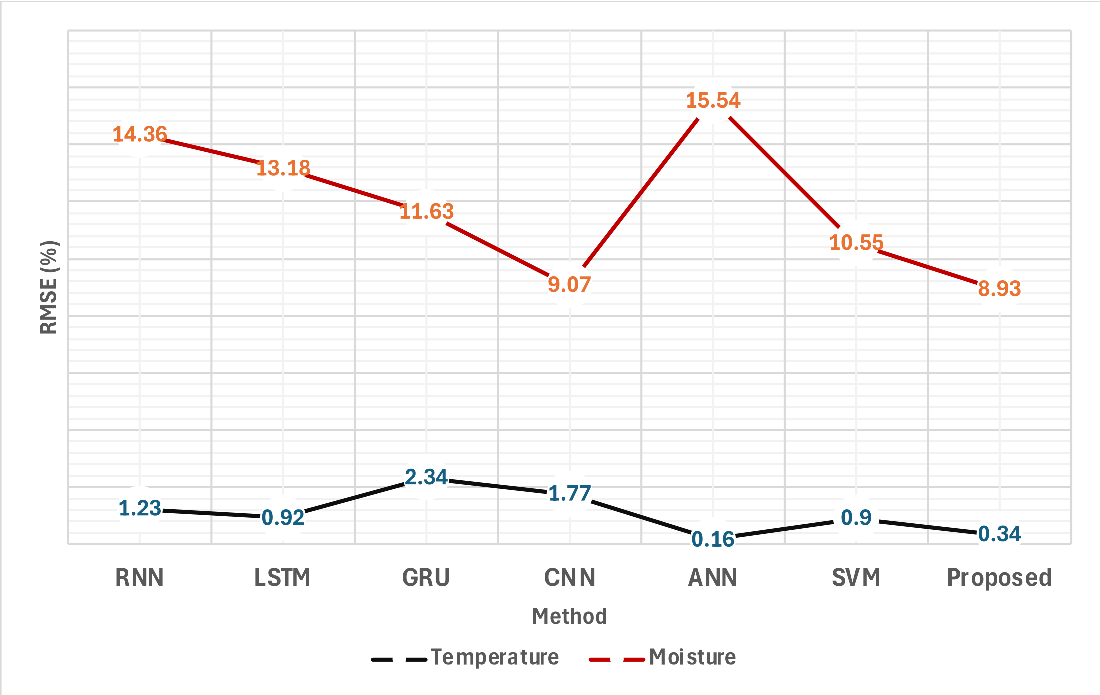


Figure 5. Root mean square error (RMSE) analysis

Conclusions: Accurate forecasting of meteorological data is crucial for enhancing the efficiency of the PA-based IoT system. The DL method possesses autonomous learning characteristics and outstanding accuracy in intricate sensor information for BT-based IoT systems. This work employed a two-level sequential deconstruction architecture to break down the weather information for BT-based IoT systems at different times. This approach helped to simplify the intricate nonlinear relationship of the raw sensor information. By employing numerous GRUs as sub-predictors, the forecasting outcomes of these sub-predictors were ultimately merged to provide long and mid-term forecasts of weather data. By validating actual data, the model suggested demonstrates superior accuracy in forecasting and effectively fulfills the requirements of PA in BT-based IoT systems. Implementing the BT-based IoT systems in PA can significantly alleviate farmers' burden and enhance their understanding of using PA instruments. The research highlights the significance of long-term weather forecasts in guiding the scheduling of crop development cycles. It can assist farmers in the management of their agricultural operations. It is possible to provide an initial prediction and assessment of extreme weather conditions in agriculture to minimize risks and maximize profits.

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References

Akilan T, Baalamurugan KM (2024) Automated weather forecasting and field monitoring using GRU-CNN model along with IoT to support precision agriculture. Expert Syst Appl 249, e123468.

Angin P, Anisi MH, Göksel F, et al. (2020) Agrilora: a digital twin framework for smart agriculture. J Wirel Mob Netw Ubiquitous Comput Dependable Appl 11(4), 77-96.

Barron HC, Auksztulewicz R, Friston K (2020) Prediction and memory: A predictive coding account. Prog Neurobiol 192, e101821.

Boursianis AD, Papadopoulou MS, Diamantoulakis P, et al. (2022) Internet of things (IoT) and agricultural unmanned aerial vehicles (UAVs) in smart farming: A comprehensive review. Inter Thin 18, e100187.

Camgözlü Y, Kutlu Y (2023) Leaf Image Classification Based on Pre-trained Convolutional Neural Network Models. Nat Eng Sci 8(3), 214-232.

Choi J, Zhang X (2022) Classifications of restricted web streaming contents based on convolutional neural network and long short-term memory (CNN-LSTM). J Internet Serv Inf Secur 12(3), 49-62.

Cisternas I, Velásquez I, Caro A, Rodríguez A (2020) Systematic literature review of implementations of precision agriculture. Comput Electron Agric 176, e105626.

Devi T, Deepa N, Gayathri N, Rakesh Kumar S (2024) AI-based weather forecasting system for smart agriculture system using a recurrent neural networks (RNN) algorithm. In book: sustainable management of electronic waste. pp. 97-112.

Gao P, Xie J, Yang M, et al. (2021) Improved soil moisture and electrical conductivity prediction of citrus orchards based on IOT using Deep Bidirectional LSTM. Agric 11(7), e635.

Ghotbaldini H, Mohammadabadi MR, Nezamabadi-pour H et al. (2019) Predicting breeding value of body weight at 6-month age using Artificial Neural Networks in Kermani sheep breed. Acta Scientiarum Anim Sci 41, e45282.

Jung J, Maeda M, Chang A, et al. (2021) The potential of remote sensing and artificial intelligence as tools to improve the resilience of agriculture production systems. Curr Opin Biotechnol 70, 15-22.

López Rivero AJ, Martínez Alayón CA, Ferro R, et al. (2020) Network Traffic Modeling in a Wi-Fi System with Intelligent Soil Moisture Sensors (WSN) Using IoT Applications for Potato Crops and ARIMA and SARIMA Time Series. Appl Sci 10(21), 7702.

Mohammadabadi M, Kheyrodin H, Afanasenko V, et al. (2024) The role of artificial intelligence in genomics. Agric Biotechnol J 16(2), 195-279.

Nabeesab Mamdapur GM, Hadimani MB, Sheik AK, Senel E (2019) The Journal of Horticultural Science and Biotechnology (2008-2017): A Scientometric Study. J Internet Serv Inf Secur 9(1), 76-84.

Peeriga R, Rinku DR, Bhaskar JU, et al. (2024) Real-Time Rain Prediction in Agriculture using AI and IoT: A Bi-Directional LSTM Approach Eng Technol Appl Sci Res 14(4), 15805-15812.

Pour Hamidi S, Mohammadabadi MR, Asadi Foozi M, Nezamabadi-pour H (2017) Prediction of breeding values for the milk production trait in Iranian Holstein cows applying artificial neural networks. J Livestock Sci Technol 5(2), 53-61.

Saleem RM, Bashir RN, Faheem M, Haq MA et al. (2023) Internet of things based weekly crop pest prediction by using deep neural network. IEEE Access 11, 85900-85913.

Sarma KK, Das KK, Mishra V, et al. (2022) Learning-aided system for agriculture monitoring was designed using image processing and IoT-CNN. IEEE Access 10, 41525-41536.

Sumarudin A, Ismantohadi E, Puspaningrum A, Maulana S et al. (2021) Implementation irrigation system using Support Vector Machine for precision agriculture based on IoT. IOP Conf Ser: Mater Sci Eng 1098(3), e032098.

Surendar A, Veerappan S, Sindhu S, (2024) A Bibliometric Study of Publication- Citations in a Range of Journal Articles. Indian J Inf Sources Serv 14(2), 97-103.

Yin H, Cao Y, Marelli B, et al (2021) Soil sensors and plant wearables for smart and precision agriculture. Adv Mater 33(20), 2007764.

Zheng C, Li H (2023) The prediction of collective Economic development based on the PSO-LSTM model in smart agriculture. PeerJ Comput Sci 9, e1304.

Zoran G, Nemanja A, Srđan B (2022) Comparative Analysis of Old-Growth Stands Janj and Lom Using Vegetation Indices. Arch Tech Sci 2(27), 57-62.

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مدل بیوتکنولوژیکی کشاورزی پایدار و دقیق با استفاده از الگوریتم یادگیری عمیق

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چکیده

هدف: با کمک داده‌های آب و هوا از روش کشاورزی اینترنت اشیا (IoT) می‌توان برای تغییرات آب و هوایی برنامه‌ریزی کرد. این یک راه عالی برای آماده‌سازی و پیگیری تولید کشاورزی سبز است. بنابراین، هدف از این مطالعه، دقیق‌تر کردن پیش‌بینی اطلاعات آب و هوا در سیستم کشاورزی دقیق (PA) بود.

مواد و روش‌ها: پیش بینی دقیق روندهای آینده دشوار است زیرا داده‌ها پیچیده هستند و به پیوندهای خطی ساده نیاز دارند. تکامل فناوری ارتباطات و افزایش تعداد چیزهای به هم پیوسته تأثیر عمیقی بر بخش کشاورزی داشته است. پیشرفت‌های هوش مصنوعی و به‌ویژه یادگیری عمیق، پردازش سریع‌تر و دقیق‌تر داده‌ها را در این عصر دیجیتال مدرن تسهیل کرده است. یک فناوری جدید تجزیه و تحلیل داده‌ها به نام یادگیری عمیق، این پتانسیل را دارد که کشاورزی را کارآمدتر، سازگار با محیط زیست و قابل پیش‌بینی‌تر کند. در این مطالعه از پیش‌بینی‌های یادگیری عمیق (DL) با ساختار تجزیه دو سطحی و بیوتکنولوژی (BT) برای پیش‌بینی اطلاعات آب و هوا در سیستم کشاورزی دقیق (PA) استفاده شد. ابتدا داده‌های آب و هوا به چهار قسمت تجزیه شد. سپس، سیستم‌های واحد بازگشتی گیتی (GRU) به عنوان پیش‌بینی‌کننده‌های فرعی برای هر بخش ایجاد شدند.

نتایج: ابتدا داده‌های آب و هوایی به چهار قسمت تجزیه شد. سپس، سیستم‌های واحد بازگشتی گیتی (GRU) به عنوان پیش‌بینی‌کننده‌های فرعی برای هر بخش ایجاد شدند. پیش‌بینی‌های آینده میان‌مدت و بلندمدت با ترکیب نتایج GRU انجام شد. با استفاده از داده‌های آب و هوایی از سیستم‌های IoT مبتنی بر BT، تأیید شد که آزمایش‌ها با ساختار پیشنهادی کار می‌کنند.

نتیجه‌گیری: روش پیش‌بینی پیشنهادی می‌تواند دما و رطوبت را به درستی پیش‌بینی کند و استانداردهای PA را برآورده کند. می‌تواند به کشاورزان در مدیریت عملیات کشاورزی خود کمک کند. همچنین می‌توان پیش بینی و ارزیابی اولیه شرایط آب و هوایی شدید در کشاورزی را برای به حداقل رساندن خطرات و به حداکثر رساندن سود ارائه داد.

واژه‌های کلیدی: بیوتکنولوژی، پایداری، کشاورزی دقیق، یادگیری عمیق

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