CARPATHIAN JOURNAL OF FOOD SCIENCE AND TECHNOLOGY

Journal home page:**http://chimie-biologie.ubm.ro/carpathian_journal/index.html**

ENHANCING CROP YIELD PREDICTION IN PRECISION AGRICULTURE THROUGH SUSTAINABLE BIG DATA ANALYTICS AND DEEP LEARNING TECHNIQUES

Vivek Parashar[1]✉, Neelam Labhade-Kumar[2], Badadapure Pravinkumar Rajkumar[3], Bhola Khan[4], Sandeep Rout[5], T. Porselvi[6], Mahammad Idrish I. Sandhi[7]

[1]Department of Computer Science and Engineering, Amity University Madhya Pradesh.
[2] Shree Ramchandra college of Engineering, wagholi pune
[3] YSPM's Yashoda Technical Campus Wadhe Satara
[4] Department of Economics, Yobe State University, Damaturu, Nigeria
[5] Department of Agriculture, Sri Sri University, Cuttack, 754006, Odisha, India
[6] Department of EEE, Sri Sairam Engineering College
[7] Sankalchand Patel University, Visnagar
✉vivekparashar@rediffmail.com

https://doi.org/10.34302/SI/237

Article history:
Received
04 July /2023
Accepted
04 October 2023

Keywords:
Deep learning predictor;
Precision agriculture:
Internet of things;
Decomposition structure;
Prediction.

ABSTRACT

Sustainable agricultural production can be planned and managed with the use of meteorological data collected by a farming Internet of Things (IoT) system. However, forecasting future trends with accuracy is challenging. Since complex nonlinear relationships with several components are a constant feature of data, in this research using a deep learning predictor with a sequential two-level decomposition structure, in which the data of weather had been split into 4 components sequentially, while recurrent gated (GRU) served as the component sub-forecast throughout training.. As a result we found, the agricultural IoT system may make more precise weather predictions. Finally, medium and long-term prediction findings were produced by GRUs' results combination. The experiments for the proposed model were validated using data of weather through Internet of Things system (IoT) in Ningxia (China), to obtain the planting of wolfberries. The results of tests of prediction discloses the suggested predictor could obtain temperature & humidity predictions accurately and satisfying requirements of precision production in agriculture.

1. Introduction

Precision farming (PF) participation, particularly, a social and inherently complex process influenced by producers, change agents, social norms, and institutional pressure.. An empirical examination of preliminary results was done by (Mekonnen et al., 2019) Italian farmers' research revealed the importance of raising public awareness about the use of precision farming (PF) instruments and suggested that future studies should concentrate on new ideas and tactics that promote environmental sustainability. The use of internet of thing technology in this process is a crucial component. Farmers will need less information to make decisions, as a result, raising the level of agriculture as a whole. Extreme weather condition has significant effect in growth on agriculture. By looking ahead and weather prediction throughout medium term and long term, preparation can significantly cut losses. Additionally, it serves as a guide for managing a farm and insurance for agriculture.

There are several positive effects on environmental sustainability through the usage of technology like the Internet of Things (IoT) and precision farming equipment. To begin with, precision farming allows for more efficient use of resources like water, fertilizer, and pesticide. Farmers may be able to lessen their environmental effects by utilizing real-time data to pinpoint the use of these inputs. Second, the Internet of Things infrastructure allows for constant monitoring of environmental conditions. This provides farmers with the information they need to enhance agricultural operations and make choices based on evidence. As a result, fewer natural resources are used, and more people are mindful of their impact on the planet. Soil erosion, pollution, and biodiversity loss may all be mitigated by the use of precision farming practices. Integrating precision agricultural equipment with IoT technology leads to a more sustainable and environmentally friendly farming system. (Priya & Ramesh, 2020).

Sensors can collect data thanks to Internet of Things (IoT) technology, which has also given rise to critical technologies for many different intelligent systems. In past few years, the very important IoT system, the precision agricultural system enables increased production, sustainable profitability, and higher-quality goods through the use of information technology (Bhat & Huang, 2021).

The production, security, and safety of food can all be significantly improved by precision agriculture (Delgado et al., 2019). In order to make the most of energy, space, and labor, and to increase production efficiency, it is necessary to optimize resource utilization., a key area of study of IoT systems used in precision farming is offering a particular atmosphere for efficiency in accordance with climatic factors such as humidity, temperature, etc. The medium-term and long terming weather forecasts accurately assist farmers, distributors, and regulators to make choices for long-term stability in the farming sector, which supports operations that improve the positive effects utilizing and expanding access to food on individuals, communities, and economies. Future analysis in weather and modeling techniques can aid in the prediction of potential agricultural management, assisting and directing the management of production toward the development of sustainable agriculture.

Improved agricultural production forecasting is possible because of the employment of sustainable big data analytics and deep learning technology in precision agriculture. Sustainable big data approaches may be used to evaluate large amounts of agricultural data like as weather, soil moisture, and crop characteristics to get a better understanding of the elements that affect crop yield. Very precise estimates of agricultural production are now attainable because of too deep learning methods like convolutional neural networks (CNNs) and recurrent neural networks (RNNs). These methods increase prediction precision by accommodating a variety of input formats and modeling nonlinear interactions. The future viability of agricultural systems is progressively being guaranteed by the incorporation of sustainable techniques. These methods increase crop yields while decreasing agriculture’s negative environmental effects.

Due to the inherent complexity of nonlinear interactions between the numerous substances in sensor data., making predictions based on weather data is challenging. On the other hand, the IoT system's ability to gather and store vast amounts of data due to its high sampling frequency allows for the Analysis of sensory data, the discovery of new knowledge, and the prediction of future insights (A. Sharma et al., 2021).

The challenge of prediction for gathering time-sequential data generated by IoT system's sensors has been addressed using some ways. Examples of techniques used to model and forecast time sequential data's future included conventional ARIMA (auto-regressive integrated moving averages), synthetic neural networks (SNN) (R. Sharma et al., 2020), support vector machine (SVM) & particle swarm optimisation (PSO) in an echo state network (ESN). However, these models cannot provide accurate predictions for the real-world IoT system because of the peculiarities of the gathered data and the lack of modelling support for nonlinearity..

In a recent study deep learning systems described sufficient benefits for extraction of characteristics by nonlinear complex data. Particular neural network architectures, such as convolutional neural networks (CNNs) (Zhang et al., 2021) and recurrent neural networks (RNNs) and their enhanced models (Raj et al., 2021), have been used to extract characteristics of time sequential datas. These architectures include the long short term memory system (LSTM), a recurrent gated unit system (GRU), and a bidirectional long short term memory (BiLSTM) network.

For instance, newly created BiLSTM (Tantalaki et al., 2019) improves LSTM performance by feeding the network 1 step of data of time sequence both in forward and backward orientations. Amount of data that BiLSTM takes into account expands even though additional rounds of training are needed and there are more parameters. In addition, (Shakoor et al., 2019) suggested a technique called GRU that enhanced LSTM system by removing a restricting units and tests revealed that GRU system having made more progress than LSTM system even its efficient form are used . In order to produce a more precise long-term prediction,(Perakis et al., 2020) merged conventional technique ARIMA with GRU system validating by using the data of Beijing 2.5pm

To satisfy the objectives of precision agriculture, the efficiency of these networks must be improved in order to obtain more precise meteorological data predictions. Researchers concur that the fact that the obtained information on the weather from the IoT system constantly has various components is one of the factors contributing to the decline in prediction performance.

As an illustration, the temperature data often include four different types of substances/components including:

1) Trend components: Primary trend axis of data of temperature is shown by such term. The linear growth and fall trend are frequently included in this section.

The temperature fluctuations over a lengthy period of time are reflected in the trend component.

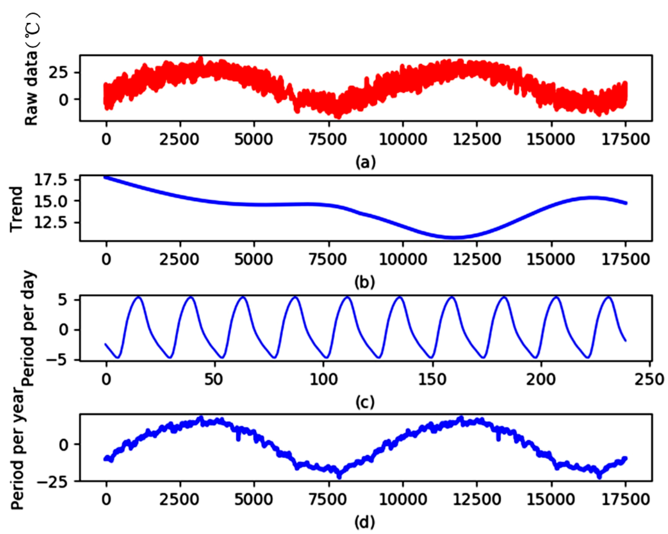

Figure 1. Data about the temperature in Ningxia, China, broken down adapted from (X.-B. Jin et al., 2020)

(2) Periodic components per day: There are clear period features in the temperature data, with a value during the day being greater and a value during the night being lower.

(3) Duration components per year: There is another period in the temperature data that corresponds to the temperature cycles in the four seasons of the year.

(4) Remnant component: This is the portion of the initial information that is left after the trend and period components have been

removed, and it typically comprises complicated nonlinear elements and noise.

In the first subfigure of Figure 1a, a sample of hourly temperature readings from Ningxia, China, from January 2016 to December 2017 is shown. While sampling, intervals set on 1 hour and observation points are represented by abscissa axis [Figure 1].

Figure 1 depicts annual temperature fluctuations that are likely representative of those observed in Ningxia, China. The "duration" part of temperature data refers to how long certain temperature patterns or trends were found to persist. We may learn about annual temperature swings in Ningxia by focusing on the duration component. It's possible to learn things like the average length of the summer, the average length of the winter, the average length of time between seasons, and the average length of time for temperature variations. Predicting crop yields and scheduling agricultural operations within the framework of precision agriculture benefit greatly from the knowledge of seasonal trends and temperature fluctuations.

Figure 2: The second subfigure's trend component during this time, 1b) is between approximately 10 and 17.5 degrees. Figure 1c, the third subfigure, displays periodic element in per 24 hours. We observed that variation in temperature during day shows a clear periodicity of every day. We display data for a period of 10 days, or roughly 240 hours, to vividly depict the time each day lasts. According to the graph, the temperature starts to climb in the early morning hours and starts to fall afternoon.

However, the bottom subfigure of Figure 1d depicts the period per year where the four seasons' apparent variations may also observed. Average of summer temperature higher than average of temperature in winters.

As a result, there are two times throughout the whole year when temperature changing: during change from day to night and during the four seasons. Similar patterns of change can be seen in further climate information, likewise related humidity.

Figure 1: Data about the temperature in Ningxia, China, broken down adapted from (X.-B. Jin et al., 2020)

Research have demonstrated about breakdown is such an efficient way to developing prediction since network still are unable to extracted the complicated non-linearity of that multicomponent analysis. So, data are divided in several substances that lessen complexity.(Islam Sarker et al., 2019) applied a decomposition method for seasonal data breakdown for easier analysis and interpretation. In order to assess a trend's potential impact on variations in pollen counts, comparing to observed variations in land usage as one moves out from the city. The decomposition technique proved to be quite successful in separation of trend component from data of time sequence. By using the decomposition method, Jess et al. (Fenu & Malloci, 2020) pollen concentration sequencing data was split up into residual and seasonal groupsThe residuals were then fitted using partial least squares regression, and a time-sequential model of airborne pollen was developed to predict the daily intensity of pollen The pattern in the corrected time series data was estimated by (Bhakta et al., 2019) using maximum likelihood estimation, which increased the forecasting data accuracy. (Palanivel & Surianarayanan, 2019) LOESS (STL)-based trend decomposition seasonal processes were linked with echo state networks (ESN), for the predicted flow of passenger and two passenger flow prediction applications depends upon railway and air data, they carried out to assess efficiency and feasibility of method capability of the suggested methods.

We continued in this deconstruction process, and the following are our novel contributions:

(1) To determine the data's periodicity per day and per year, we deconstructed the data using a sequential two-level structure according to the properties of weather data.

(2) Sub-predictors are created based on four GRUs for decomposed trend, period, and durations, and we provide a basic forecasting framework for IoT that produce reliable forecast of weather information, this may better extract the weather data's periodic properties, reduce the breaks down complexity of components, and boost the accuracy of forecasts. By reducing the input and output dimensions and extending the

forecast to the following day, results of the sub-predictions combined to produce an reliable hour forecasting of humidity & temperature for following day per hour. This was done using the pick-up-data method.

Here is how the rest of the essay is organized as: the research goal is demonstrating in [Section 2], along with the experimental data. In Section 3, the predictor is put forth, particularly the two-level decomposition and structure of the model of prediction. The experiment findings are shown in Section 3, along with data of humidity with temperature from a wolfberrys planting in Ningxia, China. The findings support the usefulness of the proposed framework. The paper is summarized and concluded in Section 4.

1.1 Literature Review

Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) are two deep learning approaches that might improve crop production prediction models used in precision agriculture. This is because these networks are better able to pick up subtle connections and trends in agricultural data. In the context of crop monitoring and disease diagnosis, CNNs excel in extracting useful characteristics from satellite shots or plant images. However, RNNs are especially well suited to the job of properly projecting crop growth and production based on past data from weather and sensors because they can consistently identify temporal correlations in time series data. Precision agriculture relies on accurate predictions, and deep learning methods facilitate the handling of huge and diverse datasets necessary for such applications.

Many different technologies, such as the Internet of Things and machine learning, are being used to develop tools like data analysis and decision support systems., has already resulted in a great deal of activity in field of precision agriculture. Following are the three sections into which we separated the literature review:

1) IoT/sensor network.

2) Data analysis application for Internet of Things.

3) Data analysis as smart systems in agriculture.

In the subsections below, the literature's contributions to precision in many domains are covered in detail below:

1.1.1. IoT/Sensor Networks

Wireless sensor networks are used in a wide variety of agronomic uses such as remote monitoring of soil and environmental parameters to predict crop health. A schedule for agricultural irrigation

By using WSN as an observer of environment factors such as 1) stress, 2) humidity, 3) temperature, 4) soil wetness, 5) soil salinity, and 6) soil conductivity, fields are projected. Numerous studies have been conducted, and the major contributions of numerous scholars are highlighted in the literature. The scalable network design was suggested by authors in (Dakir et al., 2022) as a way to monitor and manage crops in rural areas. They suggested control system depends on Internet of Things for the advancement of agriculture and farming. All the system upgrades and parts are looked at and scrutinized from every angle.Energy efficiency, reduced latency, and high throughput were all achieved by the routing and MAC solution in the IoT.The system combines a fog computing solution with a wireless internet-enabled long-range (WiLD) network to achieve this performance. For the purpose of setting up a data collection system for identification of Apple Scab using tables of Mills in Indian state (Himachal Pradesh), authors of (El Hachimi et al., 2021) presented a WSN framework design. Internet of Things was implemented in farming to boost harvests, improve product quality, and reduce costs. They suggested and created a method that can optimally irrigate agricultural products, including homegrown veggies and lemons, through wireless sensor networks. The system proposed has three primary components that work together to regulate the impact of environmental conditions in crop fields. Web application, mobile application, and hardware (control box). The control box, which assisted in data collection, turned out to be a WSN and computerized control system. Large-scale data was gathered from the control box using a web application, and data mining association rules were used to evaluate it. The farmer was informed via the mobile application of the soil's moisture content, and if necessary, either automated or manual watering was carried out. According to data mining, the ideal temperature and humidity for homegrown lemons and veggies are 29°C and 72°F, respectively. There are several ways in which agricultural output and efficiency might be enhanced by the use of sustainable big data analytics and deep learning technologies to the problem of predicting crop yields. There are several routes to actualizing these possibilities. To begin, technological advancements have made it simpler to filter through mountains of varied agricultural data in search of patterns and insights that might lead to better agricultural practices. In order to accurately predict crop yields, deep learning techniques like convolutional neural networks (CNNs) and recurrent neural networks (RNNs) are superior. Thirdly, farmers may be able to better manage their resources and produce less waste than they did in the past by utilizing IoT technology to gather and analyze data in real-time. Furthermore, sustainable big data analytics need to encourage the adoption of green agricultural techniques. This will aid in reducing farms' carbon footprints, making them more self-sufficient. Long-term, these developments might boost agricultural yields, resource utilization rates, and precision agriculture profits. The Smart node system, which has been developed by the authors of (Ayoub Shaikh et al., 2022) , is a precision agriculture system that is cost-effective. They used an infrastructure of software and hardware that enables the monitoring of agroclimatic factors for the best possible crop development. To boost the crop's yield, they installed the system in the field. The important purpose was using a framework to notify farmers when downy mildew illness in a vineyard context would be best treated. Senviro system has developed for grape field monitoring, adhering to IoT. They reduced communication between endpoints by utilizing the edge computing paradigm. The authors of (Elavarasan & Durai Raj Vincent, 2021) demonstrated the unreliability and expense of the current systems. Information on using the Internet of Things and machine learning in precise farming for disease prediction was offered. They suggested a system concept that included IoT and machine learning. They used environmental sensors, such as those for temperature and humidity, to gather data. The finished product was generated and then sent as an SMS to the nearby farmers. In (Zeng et al., 2022), the authors reviewed agricultural WSN-based applications. Different wireless communication technologies including Wi-Fi, Bluetooth, GPRS, Lora and ZigBee etc were compared by the authors. Because of their acceptable range of transmission and minimal energy requirements, they demonstrated that wireless communication technology like LoRa or ZigBee are particularly effective when used for Precision Agriculture. There is a categorization of numerous methods and techniques for maximizing the efficiency of wireless sensor network in terms of energy use. The methods that can be applied in PA have also been described. Also discussed are the difficulties and restrictions faced by WSNs in PA. Coupled machine learning techniques alongside the Iot that demonstrated how these techniques could be used in next-generation networks.They created a Public Safety IoT ecosystem represented as (PS-IoT) by combining the use of Unmanned Aerial Vehicles (UAV) and Wireless Powered Communication (WPC) to increase the utilization of energy in NOMA. A creative service process based on the IoT cloud computing platform and can help accelerate computing in the IoT and improve cloud-to-physical network connectivity. This study applies cutting-edge platform technologies to the cloud agriculture platform. Even in the face of scarce network data, farms can be connected and automated with tools like automated crop monitoring and picture analysis for pest management, through the application of cloud integration to vast area data collecting and Analysis, authors described an IoT system depends upon the design of a unique sensor called it as "NPK" Nitrogen Phosphorus Potassium sensor consisting of Light Dependent Resistor and light-emitting diodes. To monitor and assess the soil's nutrient status, a colorimetric method is used. The information gathered from fields is kept in a Google Cloud database for quick retrieval.

Python is used to build hardware and software designed to work together for microcontroller on the Raspberry Pi 3. The suggested model has been tested on three distinct types of soil including red soil and soil of dessert as and mountains. The devised system produced change proportional to the concentration of the soil solution. The use of SN is creating the usage of Qualnet simulator in order to examine the NPK sensor performance. When compared to existing alternatives, the built IoT was proven to be the most beneficial to farmers so that they can grow crops with a high yield

The most significant IoT applications have been recognized by researchers, and a thorough survey has been conducted with a focus on precision agriculture.

Issues encountered when utilizing IoT in smart farming. To examined protocols, techniques, and applications in the IoT, an emerging field. New taxonomies for Iot of Things technologies are mentioned in the article. It brings to a close the most important technological advancements that have the potential to significantly improve people's lives, particularly those of the old and the disabled. This work has thoroughly and exhaustively explored significant techniques, transitioning from sensors to software, in comparison to similar survey papers. Authors have suggested a survey of the most important historical architectures in (Roberts et al., 2021). In addition, the necessary component technologies to fulfill IoT application needs are broadly acknowledged.. They give a classes that shows how well-suited the suggested designs are for IoT features. Additionally, they have emphasized the benefits of current approaches and suggested new directions depends on current art state. In a further investigation, they hope to devise a plan to remedy the IoT's problems at each of the Internet's tiers. The use of WSN-connected innovative sensing and communication devices in agronomy applications is heavily stressed. To investigate the current remedies suggested in the literature, they cited various case examples. In the literature review, it is highlighted how precision farming has been used all around the world, including in India. By presenting (K & R, 2021) future approaches using cutting-edge technologies, they have illustrated the shortcomings of these current solutions. Authors examined the IoTuses in agricultural precision. They monitored the greenhouse on-site using wireless communication equipment. They suggested (Andronie et al., 2021) a wireless remote monitoring device for greenhouses. System management has been considered in the design of an information management system. Research has made use of field data. The wireless monitoring system accurately sensed greenhouse field data, which is “humidity and temperature”, and after doing the necessary research, the system produced good conditions for vegetable growth. Performance and reliability have both risen as a result of the suggested solution. The system's user interface was simple enough for regular farmers to utilize. An approach for effective crop monitoring for agricultural fields. Data may be kept and accessed from anywhere with IoT applications. Several sensors are employed to track and gather data on field conditions (Ukhurebor et al., 2022). Through GSM technology, the farmer is supplied with information about the state of the farm as a whole. The sensor component of the proposed effort is restricted to crop monitoring alone. The authors' study has concentrated on gathering data using different technologies from agricultural fields. WSN, IoT, forecasting devices, cellphones, aerial vehicles, and imaging equipment were all found to be useful during their investigation.. Additionally, the authors improved the IoT platform known as SmartFarmNet. This was capable of analyzing the field data gathering for a number of different characteristics, including soil, water, temperature, irrigation, soil moisture and fertility. The given approach can link data that had been examined and predict crop status. How have German farmers been able to accept precision farming utilizing modern technology like smartphones? According to a regression study, precision agriculture has a good impact on farmers. The authors have provided several recommendations for future IoT-based agricultural research.

1.1.2. Data analysis applications for IoT

Before the age of computers and the Internet,, several conventional techniques were used, such as manual crop disease and pest detection and statistical computations to analyses amount and forecast crop production and loss. Which is typically difficult, and as inspectors lack experience, this leads to human mistakes. Technology has the capacity to learn from experiences thanks to machine learning.

We can extract the most significant findings from the vast amounts of crop field data using data analytics and machine learning. It makes hidden patterns and connections between factors impacting horticulture, such as temperature, soil salinity, and humidity, apparent. Artificial Neural Networks (ANN), logical Regression (LR), Support Vector Machines (SVM) are most commonly using machine techniques for prediction of diseases of crops when weather data is analyzed. Using machine learning classification techniques, writers in proposed a system for classifying apple illnesses. They use photos of apple tree leaves as their input to classify two diseases: apple scab and marsonina coronaria.

The simulation system proposed was simulated using MATLAB 2016. They demonstrated that the K nearest neighbour accurately classified illnesses with an accuracy of 99.23%. This system was created in Uttarakhand (Himachal Pradesh). The authors of (Jung et al., 2021) demonstrated the unreliability and expense of the current systems. They provided information on how to use IoT to anticipate crop illnesses. They suggested a system concept that included IoT and machine learning. They used environmental sensors, such as those for temperature and humidity, to gather data. The finished product was generated and then sent as an SMS to the nearby farmers. Intelligent machine learning techniques have been applied to enhance quality of service of constrained wireless technology. Sensor devices placed in farm fields that provide data to a central gateway were used to collect environmental characteristics, including temperature and humidity. The information gathered aids in identifying the severity and risk of bloom.

In order to anticipate the site-specific yield, writes in utilized image processing and information analysis techniques for precision agriculture. They demonstrated that there's a strong relationship between blossom density and fruit output by accurately forecasting the apple orchard's yield with a rate of more than 79.8%. Five on-site weather stations that gather data have been set up in orchards. The gathered information can be incorporated into models to forecast the times of apple scab infection. These models can assist farmers in determining if fungicide applications to manage apple scabs are necessary (or not). They published the data on http://www.pomosat.ro so that Romanian apple growers in the area could approach and using it to inform their decisions. The suggested model is based on time series prediction and artificial intelligence. Instead of adding up the length of wetness, the apple scab infection period was considered as the time series prediction model. Utilizing feature selection techniques, significant hours were identified. Fisher's Linear Discriminant Analysis, Pearson's Correlation Coefficient, and Adaptive Neuro-fuzzy Classification with Linguistic Hedges.

The model of an adaptable neural network performed the prediction. Measurements must be taken for 24 hours in order to establish the severity of the apple scab infection. Relative moisture, leaf wetness, temperature, daylight hours, and rainfall are five meteorological metrics. Data was gathered every 12 minutes, so time was included as a further variable for time series prediction. They noted a connection between meteorological readings and apple scabs.

DSS was able to calculate the exact amount of fungicide to use. In addition, weather-related IoT sensors were set up to gather real time data, then forwarded to process on an IoT cloud system. For the purpose of forecasting late blight, the weather data collected by weather monitoring stations was incorporated into the model for the forecast.

For farmers, the approach proved quite effective and economical. By using sensory systems, authors of aimed to arrange heterogeneous data coming from various sources into datasets. They also demonstrated the value of businesses' efforts to increase profitability, whether they are large or small, public or private.

The best chance of achieving goals is to learn how to use continuously gathered data in the right manner. It suggested the usefulness of machine learning, neural networks, and regression analysis in making decisions. The value of smart phones in agronomy for collecting data on a wide range of variables, including moisture in soil, moisture in air and temperature etc. The benefits of smartphones in the agriculture sector are mentioned in the same article. To find out what the farmers desired, the writers interviewed and administered questionnaires to 230 or so of them. They reached the conclusion that farmers are interested in using smartphones to obtain information on recent farm data after completing the process.

1.1.3. Data Analysis as smart systems in Agriculture

Internet of Things is crucial for gathering information in real time in precision agriculture. Improve farming methods through the use of real-time data collected from crop fields, nodes of IoT sensors can make the system more useful system exact. The agriculture system is made more practical by adding data analytic. These technologies are all quite useful in different industries. To keep farmers up to date on the status of their crops, a variety of applications are being developed for them in precision agriculture. Generally, there are three main stages in a precision agricultural architecture, soil and plant health, as well as other physical or environmental parameters can be monitored by many sensors and Internet of Things nodes are used in the first stage. For example, a soil moisture sensor records soil wetness readings, and a soil nutrient sensor evaluates the soil's fertility. Data is collected precisely in second stage. Depending on the requirements, Data can be sent to the cloud for more complex processing and remote monitoring, or it can be stored locally at the nearest fog node. The last stage of the design employs analytical techniques to determine the condition of crops field. The end users (farmers) are then informed of this information, which enables them to determine whether the measurement is either below or above the thresholdAs a result, they initiate contact with the actuator that activates the watering system. Alternatively, the farmers balancing the fertility of soil by sprinkling the organic fertilizers. Upon detecting (sensing/predicting) any critical scenario, an activation mechanism using actuators and analytics is triggered.

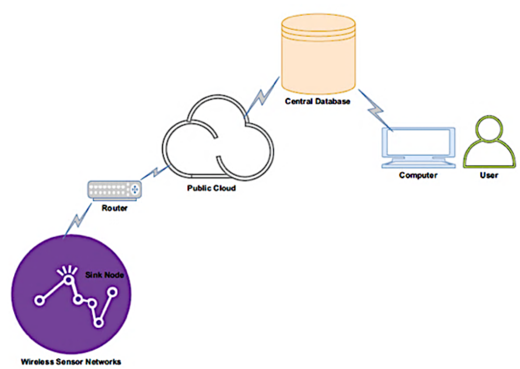

Figure 2. Precision Agriculture Model adapted from (Raj et al., 2021)

There are several Internet of Things applications in precision agricultural system, some of which are listed here. Precision agriculture uses are depicted in Figure 2.

Figure 2 depicts an Internet-of-Things system that relies heavily on a deep learning algorithm to predict future temperatures and humidity levels based on historical data. The algorithm is "trained" using a massive database of past temperature and humidity readings. All of this "training" is done using archived information. Due to the training process, the algorithm is able to learn new insights into the data. Once the algorithm has been trained, it will be able to generate real-time predictions based on data collected by the temperature and humidity sensors that are part of the IoT system. The system's use of deep learning methods allows for a more thorough comprehension of the interdependencies between the variables, leading to more precise predictions for application in precision agriculture.

2. Metodolog

2.1. Research Objectives and Data Description

In China's Ningxia province, a wolfberry farm started using IoT technology. The province of Ningxia is home to a significant portion of China's wolfberry crop. Currently, Ningxia has a planting area of 1 million mu or 33% of the country's entire land area.

Environmental elements, including temperature, humidity, and others, have a significant impact on the survival and development of wolfberry plants. Understanding and predicting these meteorological elements is crucial to the function and effects of wolfberry precision agriculture.

In order to improve the accuracy and reliability of crop production prediction models, precision agriculture makes use of massive amounts of agricultural data. More precise estimates of agricultural output are possible because of the models' ability to collect and evaluate the complex correlations and patterns resulting from a wide range of inputs such as weather patterns, soil conditions, and crop growth characteristics. This allows them to boost agricultural output by improving decision-making, resource allocation, and other related processes.

The planters can modify their planting and picking schedules in accordance with weather predictions, take full advantage of the region's abundant natural resources, and continue the planting industry's sustainable growth.

The IoT for precise agriculture is depicted in Figure 2. Sensors, such as an overview of the surface, a machine, a control unit, and an irrigate actuator, make up the majority of the IOT system. Our IoT system includes a wireless, battery-operated temperature and humidity sensor because of outside planting. This system will gather temperature and humidity data, which will then be sent to computer for archival. Additionally, a sizable amount of previously collected information was utilized for training the deep learning algorithm in order to provide a precise forecast of future humidity and temperature. The display board's primary purpose was to show the current weather. The irrigation actuator was controlled by the controller.

The following two words predictions are required for the prediction outcomes application-specific considerations

(1) Short-term prediction: giving reliable humidity and temperature forecasts in next 12 hours

(2) long term prediction: forecasting the next 30 days' worth of average daily temperatures as well as humidity levels.

To guarantee the efficient use of water resources, the former is utilized to direct the irrigation plan for the following day. Automatic irrigation can be performed by using irrigation control, the timing and amount of which are dynamically decided based on precise humidity and temp prediction for the period of 24 hours that follows.

Then last one make use to organize picking, harvesting and other activities. These strategies, which are based on precise weather predictions, can increase agricultural sustainability.

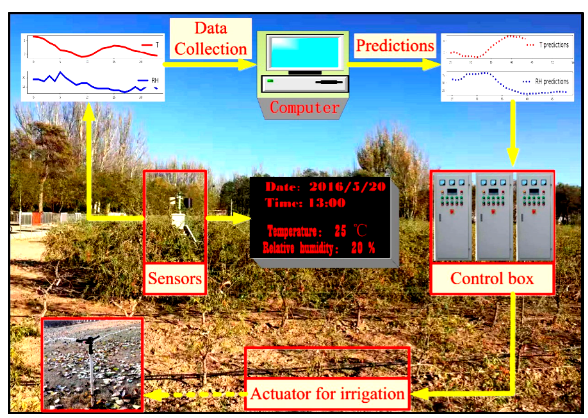

Figure 3. The Internet of Things is used for data collection and forecasting in precision agriculture adapted from (X. Jin et al., 2020).

2.2. Structured Model

The structure comprises 3 components: combination, prediction, and decomposition. Figure 3 depicts the Framework for prediction. Four distinct categories were extracted from the raw data using a two-level decomposition method. Then, every part was handled differently to produce various GRU sub predictor during network training and employed at prediction stage to forecast the various components. The final projected outcomes were then obtained by combining all the predictions and placed in the output node.

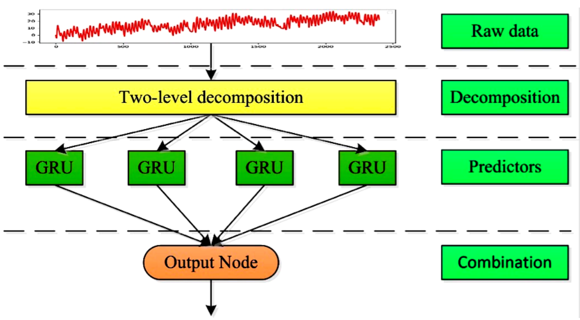

Figure 4. Structured flowchart for making forecasts adapted from (X.-B. Jin et al., 2020)

The decomposition method may be used to effectively separate continuous meteorological variables like temperature and humidity into distinct subcomponents, as shown in Figure 4. Temperature and humidity are two such examples. Periodic patterns and cycles are captured by the period component (PDt), whereas trends are represented by the trend component (TDt). The residual component (RDt) captures this kind of random or unexpected data fluctuation that is independent of both the trend and the time period.

2.3. Two-Level Decomposition Sequence

The underlying time series data was divided into two levels sequentially. Twenty-four hours were used as the trend, daily period, and residual were identified using first-level decomposition.

Since the first-level decomposition's residue still exhibited periodicity, we applied The remainder split into three more components using second-level decomposition.

The division of the node in Figure 3 is depicted in further depth in Figure 4. First-level decomposition was used to partition meteorological variables like temperature and humidity into three sub-components: 1) the trend (TDt), the period (PDt),the residual (RDt). The residual (RDt) was then further broken down into (TYt), (PYt), and (RYt).

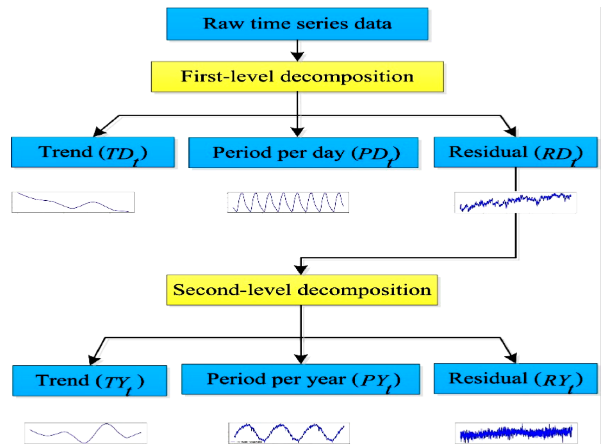

Figure 5. The structure of sequential two-level decomposition adapted from (X. Jin et al., 2020) .

2.4.Decomposition First Level

At the first level of decomposition, the trend component (abbreviated TDt) is extracted using a mean regression strategy. This is done so that the dominant trend in the time series may be represented faithfully. The raw data (Dt) may be subtracted from the trend component (Tc) to provide the period component. The result is the period difference (PDt). Any points between 1 and n may be used to get the first-period curve. You may use this curve to make estimates for the beginning of the era. Each of the twenty-four data points must be multiplied by the total number of time periods, then the sum of these products must be added together and finally, the sum is divided by the total number of time periods. By using this method, we are able to detect and provide an explanation for recurrent patterns in the data.

Time sequential data Dt is assumed to contain N observations, where t can take on the values 1, 2,.., N. The relationship between Yt and its three constituents—the trend, the period per day, and the residual—as depicted in

$$Dt = TDt + PDt + RDt \; t + N\,(1,2,\ldots.) \quad (1)$$

Where as the trend is denoted by TDt, period day is denoted by PDt, residual is denoted by RDt. The process of decomposition is given below:

- Set the period on 24 hours/day, which means 24 sample data collected. Calculate period's numbers by N/24.
- The general trend in the time series data can be reflected by extracting the trend TDt using the mean regression approach.
- Calculate component of period first from data by (XDt = Dt – TDt) to estimate initial period component. 2) Then selecting points from first to last number by multiplying twenty four in (XDt), add the data at the same time and divided by number to obtain first curve of period, then copying the Number of times and considered the difference of the (Number multiply by24) and (N) by obtaining (PDt).
- Calculate residual component (RDt) by given equation as follows

RDt = (Dt - TDt – PDt)

Time series data (Dt) is related to its trend (TDt), period per day (PDt), and residual (RDt) in Equation #1. The value of Dt, also known as the observed data, is calculated by adding these three numbers together, as shown in the formula. The period per day component (abbreviated as PDt) shows daily fluctuations, while the trend component (abbreviated as TDt) shows the overall trend in the data. Variations not explained by the daily trend or the period are attributed to the residual component (RDt). By breaking down the time-sequential data into its three constituent parts and analyzing them independently, the framework provided by Equation #1 may be utilized to improve one's understanding of the observed data.

2.5. 2nd Decomposition Level

We applied same strategy using the already-decomposed data.In above calculations we simply calculate the mean values of per day. Equation that derived the relation between residual component (RDt) with its independent components; trend (TYt), yearly period component (PYt), Residual component (RYt) are as follows:

RDt. = TY + PYt + RYt (t=1,2,….., N)

The process of decomposition is given below:

- Set the period on an year. 365 days in year multiply by 24 hours we get 8760 hours in year. Then calculate periods number by N divided by 8760 [N/8760]
- The overall trend in the time series data can be reflected by calculating the component of trend (TYt) using the mean regression approach.
- Calculate component of period from data by (XYt = RDt – TYt) (ii) Then selecting points from 1st to last Num*8760th in (XYt), add the data at the same time and divided by Num to obtain one curve of period, then copying the Num times and considered (XPYt)
- In this step we calculate the mean values of each day (each 24 hours).You can get the N-point and period component PYt by substituting the new point data, XPYt.
- Calculate component of residual (RYt) by given equation
- RYt = RDt – Tyt - PYt.

2.6. Predictor for Deep Learning

As the trend element Tt, two trends, (TDt) and (Tyt) were added. Four components, residual (RYt), the time duration per day (PDt), the timeframe per year PYt, and were utilized for (GRU) systems. These three components are being the period per day (PDt), residual RYt, timeframe per year PYt.

2.6.1. Sub-Predictor GRU

This network consists of different GRU cells, and we set the number of layers as 2. Shown as Figure 5, St, t = 1, 2, …, n is the input of the GRU network, and St+n , t = 1, 2, …..n is the output.

The gate is used by GRU to regulate how much of the preceding moment's state information is incorporated into the current state. The relationship between data input and output was modeled using the updating gates and the reset gate. Each GRU cell's forward propagation formulae are following,

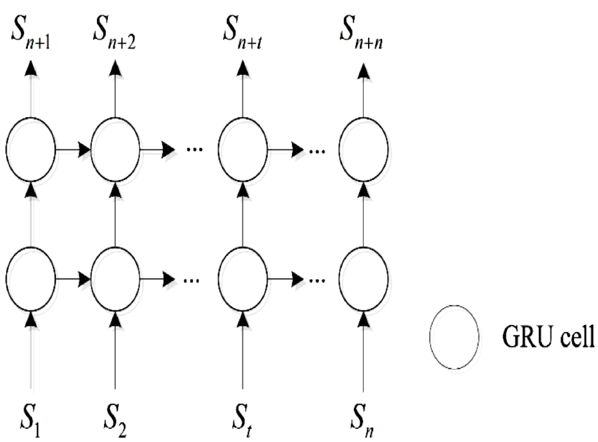

Figure 6. The organizational framework of a GRU network adapted from (X.-B. Jin et al., 2020).

In Figure 6, we can see how GRU networks employ updating gates and reset gates to symbolize the connection between input and output data for the purpose of weather forecasting. To what extent previous state data should be used to inform the present state is a function of the updating gate (zt). The level of forgetting the previous state is controlled by the reset gate (rt). The GRU network can constantly adjust the parameters of these gates to update and retain essential information, allowing it to capture intricate relationships and patterns in the meteorological data. This makes it possible to always have the most recent data available. This gating mechanism enables the GRU network to provide a very accurate description of temporal dynamics.

Where each GRU cell's input vector is represented by dt and R, and current hidden node's updated gate, reset gate, and finalist state, and current visibility status of a hidden node that is active are represented by zt, rt, ht, and ht, accordingly.

U and W are the load matrices that are learned by the model over the course of its training; b is the element-wise multiplication of the bias vectors; and tanh are the activation functions.

In order to forecast these four factors, four GRUs were developed as sub-predictors: the There is the trending part (Tt), the daily part (PDt), the yearly part (PYt), and the leftover part (RYt). In the long run forecasting, we set n to 30 and define St as the time frame per year (PYt) component. For medium-term forecasting, St uses the remaining three components, and n is set to 24. In other words, we forecasted data for upcoming twenty-four hours using the historical data from previous 24 hours. This technique can be used in other disciplines as well as other signal control and modeling systems and integrated with other system recognition techniques to examine the simulation and forecasting of other fluid time series and random systems.

In order to improve the accuracy and reliability of crop production prediction models, precision agriculture makes use of massive amounts of agricultural data. More precise estimates of agricultural output are possible because of the models' ability to collect and evaluate the complex correlations and patterns resulting from a wide range of inputs such as weather patterns, soil conditions, and crop growth characteristics. This allows them to boost agricultural output by improving decision-making, resource allocation, and other related processes.

3. Results and Discussions

Root Mean Square Error (RMSE) values that are close to zero indicate that the proposed model is very accurate in predicting future temperatures and humidity levels. Smaller values for the root-mean-square-error (RMSE) indicate better agreement between the predicted and observed values. The suggested model outperformed RNNs, LSTMs, BiLSTMs, and GRUs, as shown in the results and comments section. The suggested model has RMSEs for predicting both temperature and humidity of around 20.34 and 2.04 percentage points. These reductions in RMSE show that the suggested model is a more precise forecaster of future weather conditions than the baseline model.

The data collected hourly data on humidity and temperature with around 35,040 samples were utilized for training the model. In the tests, the split between training and testing data was 80:20.

The proposed prediction model was executed in the experiment's hardware and software environments. All learning models were created using the TensorFlow-based free deep learning framework Keras. On a computer with an Intel (CORETM 4200U i5 CPU) running at 1.60 (GHz) and (4 GB) of memory, all trials were conducted. Deep neural networks were initialized in experiments using default Keras parameters, such as weight initialization. Furthermore, the GRU model's activation functions were ReLu and tanh.

Typically, when building models with neural networks, the dimensions of the network topology and the total amount of neurons are left vague. Instead, the data are used to determine how complex the model structure should be. Through numerous experimental changes, we established the parameters for every component of the model. We utilized the ReLu function specifically. The result of the model's scale determines how many neurons per layer are used. There were two layers of GRUs, with 30 neurons in the first layer, 30 neurons in the second layer, and 24 neurons in the other GRUs. In addition, the Adam technique was used to systematically improve an existing objective function to give model parameters during the supervised training phase for all models.

There are many challenges that must be surmounted before precision agriculture can be used to reliably anticipate crop yields, including the need for real-time analysis, the scarcity of data, the complexity of agricultural data, and the inherent unpredictability of agricultural data. By effectively processing and analyzing massive amounts of data from several agricultural sources, such as information on the climate, the soil, and the crops being cultivated, sustainable big data analytics may be able to help identify answers to these difficulties. When data from Internet of Things (IoT) devices are combined with satellite photography, a more complete picture of the state of agriculture may be painted. Mining this data for useful insights using state-of-the-art analytic methods like deep learning has the potential to increase the precision of yield predictions. Data-driven decision-making receives a boost from sustainable big data analytics, which in turn allows precision agriculture to maximize yields while minimizing waste.

3.1. Other Predictors Comparison

In this study, we compared the proposed model to eight existing models, including RNNs, LSTMs, BiLSTMs, GRUs, and seasonal trend decomposition algorithms utilizing loess (STL) [19] using RNNs, LSTMs, BiLSTMs, and GRUs as the sub-predictors. Root-mean-square-error (RMSE) is a way to quantify how far off a model's forecast is from the actual data in order to assess how well that model performs as a predictor.

Where N representing the total number of prediction datasets, obs (x) represents the data gathered, and pre x represents the predicted value.

Table 1. Root mean square errors (RMSE) of predictions made using various predictors are compared

Model	(RMSE) of Temperature predictions	(RMSE) of relative humidity predictions
RNN	2.6710	14.1084
LSTM	3.0011	14.3347
BiLSTM	2.9989	14.1988
GRU	3.0104	14.6015
STL_RNN	2.7999	13.9102
STL_LSTM	2.5015	13.5925
STL_BiLSTM	2.4345	14.0025
STL_GRU	2.6781	14.2678
Proposed Model	2.5547	13.2897

RMSE compares the projected outcomes of the (RNN), (LSTM), (BiLSTM), (GRU), (STL_RNN) (STL-based RNN), (STL_LSTM) (STL-based LSTM), (STL_BiLSTM), (STL_GRU), and GRU-based bi-level decomposition. Decomposed models do substantially better than undecomposed ones when comparing prediction results, and the one being suggested forecasts results more precisely than existing models. When compared to the GRU and STL_LSTM models, the RMSEs for the proposed model's predictions of both temperature and humidity are roughly 20.34% and 2.04%, respectively.

The RMSEs for temperature, on the other hand, are 8.61% and 2.19% smaller, respectively. The results show that the RMSEs may be significantly reduced by using the GRU as the sub-predictor, indicating the efficacy of the newly developed two-level decomposition.

When comparing the RMSE for temperature and humidity forecasts, the proposed prediction model outperforms previous models like RNNs, LSTMs, BiLSTMs, and GRUs. The suggested model's RMSE value for temperature forecasts is about 8.61% lower than the findings generated by other models. Humidity forecast RMSE estimations are similarly reduced, by around 2.19 percentage points. These results suggest that the suggested model outperforms the state-of-the-art models when it comes to forecasting future temperatures and humidity levels. Evidence that the suggested model and the newly generated two-level decomposition are successful may be seen in the declining RMSE values.

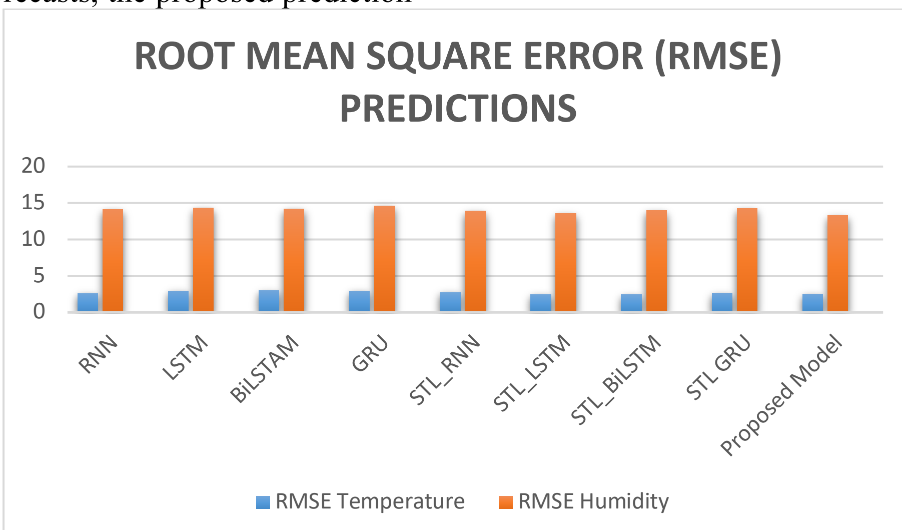

Figure 7. The (RMSE) histogram for temperature and humidity forecasting adapted from (X.-B. Jin et al., 2020)

4. Conclusions

Accurate weather data prediction is crucial to a precision agricultural IoT system's performance improvement. The deep learning method performs exceptionally well on complex sensor data and can learn for itself. In this work, the weather data were divided into separate periods using the breakdown into two levels sequentially; It simplified the nonlinear relationship present in raw sensor data. Multiple GRUs were used as sub-predictors, and their prediction results were combined to make a long as well as medium term forecasts of weather. The suggested model can match the demands of precision agriculture and has a greater prediction accuracy thanks to real data validation. Through the use of Internet of Things (IoT) technology, precision agricultural costs can be greatly reduced, farmers' familiarity with precision agriculture tools can be increased, and farmers' workloads can be lightened.. Following our study, long-term weather forecasts can offer crucial advice for organizing a good crop growth cycle. It can also assist farmers in managing their crops. For instance, an initial prediction and estimate of severe weather might be made in agriculture to lower risks and boost profitability.

Merging deep learning methods with enduring big data analytics offers a significant opportunity to improve crop output forecasts in precision agriculture. A big window of opportunity offers itself now to seize this possibility. The proposed model has a lot of benefits when it comes to making long-term and medium-term weather predictions since it uses a large number of GRUs as sub-predictors and combines the prediction outputs of these GRUs. To begin, it allows for the recording of trends in addition to daily fluctuations, annual variations, and residuals, all of which contribute to a more complete knowledge of the dynamics of the weather. Second, by using GRUs, the model is better equipped to learn from intricate sensor data and spot temporal correlations, resulting in more precise and trustworthy forecasts. Third, the model may include the predictions of the various sub-predictors to increase the overall accuracy of the forecast by making use of the talents that each individual sub-predictor has. More accurate weather predictions might allow precision agricultural technologies to improve crop management techniques. This is where the process ends up.

It is important to note the many advantages offered by the integration of big data analytics and deep learning algorithms for crop production prediction in precision agriculture. The first benefit is that it facilitates the collection and analysis of massive amounts of agricultural data, such as weather patterns, soil conditions, and crop characteristics, which in turn increases the precision and scope of forecasts. Second, deep learning algorithms are superior to more conventional approaches because of their ability to efficiently capture complicated patterns and nonlinear correlations in the data. This is because of the superiority of deep learning algorithms. In conclusion, sustainable agricultural techniques help raise harvest yields while being gentler on the environment. Because of the cutting-edge nature of these technologies, real-time tracking and decision-making are now viable options. The ability to make timely, educated decisions on crop management is a huge benefit for farmers. In conclusion, the efficiency and longevity of precision agricultural systems are enhanced by the integration of big data analytics and deep learning.

5. References

Andronie, M., Lăzăroiu, G., Iatagan, M., Hurloiu, I., & Dijmărescu, I. (2021). Sustainable Cyber-Physical Production Systems in Big Data-Driven Smart Urban Economy: A Systematic Literature Review. *Sustainability*, *13*(2), Article 2.

Ayoub Shaikh, T., Rasool, T., & Rasheed Lone, F. (2022). Towards leveraging the role of machine learning and artificial intelligence in precision agriculture and smart farming. *Computers and Electronics in Agriculture*, *198*, 107119.

Bhakta, I., Phadikar, S., & Majumder, K. (2019). State-of-the-art technologies in precision agriculture: A systematic review. *Journal of the Science of Food and Agriculture*, *99*(11), 4878–4888.

Bhat, S. A., & Huang, N.-F. (2021). Big Data and AI Revolution in Precision Agriculture: Survey and Challenges. *IEEE Access*, *9*, 110209–110222.

Dakir, A., Barramou, F., & Alami, O. B. (2022). Opportunities for Artificial Intelligence in Precision Agriculture Using Satellite Remote Sensing. In F. Barramou, E. H. El Brirchi, K. Mansouri, & Y. Dehbi (Eds.), *Geospatial Intelligence: Applications and Future Trends* (pp. 107–117). Springer International Publishing.

Delgado, J. A., Short, N. M., Roberts, D. P., & Vandenberg, B. (2019). Big Data Analysis for Sustainable Agriculture on a Geospatial Cloud Framework. *Frontiers in Sustainable Food Systems*, *3*.

El Hachimi, C., Belaqziz, S., Khabba, S., & Chehbouni, A. (2021). Towards precision agriculture in Morocco: A machine learning approach for recommending crops and forecasting weather. *2021 International Conference on Digital Age & Technological Advances for Sustainable Development (ICDATA)*, 88–95.

Elavarasan, D., & Durai Raj Vincent, P. M. (2021). Fuzzy deep learning-based crop yield prediction model for sustainable agronomical frameworks. *Neural Computing and Applications*, *33*(20), 13205–13224.

Fenu, G., & Malloci, F. M. (2020). An Application of Machine Learning Technique in Forecasting Crop Disease. *Proceedings of the 3rd International Conference on Big Data Research*, 76–82.

Islam Sarker, M. N., Wu, M., Chanthamith, B., Yusufzada, S., Li, D., & Zhang, J. (2019). Big Data Driven Smart Agriculture: Pathway for Sustainable Development. *2019 2nd International Conference on Artificial Intelligence and Big Data (ICAIBD)*, 60–65.

Jin, X., Yu, X.-H., Wang, X.-Y., Bai, Y.-T., Su, T.-L., & Kong, J.-L. (2020). Deep Learning Predictor for Sustainable Precision Agriculture Based on Internet of Things System. *Sustainability*, *12*, 1433.

Jin, X.-B., Yu, X.-H., Wang, X.-Y., Bai, Y.-T., Su, T.-L., & Kong, J.-L. (2020). Deep Learning Predictor for Sustainable Precision Agriculture Based on Internet of Things System. *Sustainability*, *12*(4), Article 4.

Jung, J., Maeda, M., Chang, A., Bhandari, M., Ashapure, A., & Landivar-Bowles, J. (2021). The potential of remote sensing and artificial intelligence as tools to improve the resilience of agriculture production systems. *Current Opinion in Biotechnology*, *70*, 15–22.

K, M., & R, R. (2021). Crop Recommendation for Better Crop Yield for Precision Agriculture Using Ant Colony Optimization with Deep Learning Method. *Annals of the Romanian Society for Cell Biology*, 4783–4794.

Mekonnen, Y., Namuduri, S., Burton, L., Sarwat, A., & Bhansali, S. (2019). Review—Machine Learning Techniques in Wireless Sensor Network Based Precision Agriculture. *Journal of The Electrochemical Society*, *167*(3), 037522.

Palanivel, K., & Surianarayanan, C. (2019). *An Approach for Prediction of Crop Yield Using Machine Learning and Big Data Techniques* (SSRN Scholarly Paper No. 3555087).

Perakis, K., Lampathaki, F., Nikas, K., Georgiou, Y., Marko, O., & Maselyne, J. (2020). CYBELE – Fostering precision agriculture & livestock farming through secure access to large-scale HPC enabled virtual industrial experimentation environments fostering scalable big data analytics. *Computer Networks*, *168*, 107035.

Priya, R., & Ramesh, D. (2020). ML based sustainable precision agriculture: A future generation perspective. *Sustainable Computing: Informatics and Systems*, *28*, 100439. https://doi.org/10.1016/j.suscom.2020.100439

Raj, E. F. I., Appadurai, M., & Athiappan, K. (2021). Precision Farming in Modern Agriculture. In A. Choudhury, A. Biswas, T. P. Singh, & S. K. Ghosh (Eds.), *Smart Agriculture Automation Using Advanced Technologies: Data Analytics and Machine Learning, Cloud Architecture, Automation and IoT* (pp. 61–87). Springer.

Roberts, D. P., Short, N. M., Sill, J., Lakshman, D. K., Hu, X., & Buser, M. (2021). Precision agriculture and geospatial techniques for sustainable disease control. *Indian Phytopathology*, *74*(2), 287–305.

Shakoor, N., Northrup, D., Murray, S., & Mockler, T. C. (2019). Big Data Driven Agriculture: Big Data Analytics in Plant Breeding, Genomics, and the Use of Remote Sensing Technologies to Advance Crop Productivity. *The Plant Phenome Journal*, *2*(1), 180009.

Sharma, A., Jain, A., Gupta, P., & Chowdary, V. (2021). Machine Learning Applications for Precision Agriculture: A Comprehensive Review. *IEEE Access*, *9*, 4843–4873.

Sharma, R., Kamble, S. S., Gunasekaran, A., Kumar, V., & Kumar, A. (2020). A systematic literature review on machine learning applications for sustainable agriculture supply chain performance. *Computers & Operations Research*, *119*, 104926.

Tantalaki, N., Souravlas, S., & Roumeliotis, M. (2019). Data-Driven Decision Making in Precision Agriculture: The Rise of Big Data in Agricultural Systems. *Journal of Agricultural & Food Information*, *20*(4), 344–380.

Ukhurebor, K. E., Adetunji, C. O., Olugbemi, O. T., Nwankwo, W., Olayinka, A. S., Umezuruike, C., & Hefft, D. I. (2022). Chapter 6 - Precision agriculture: Weather forecasting for future farming. In A. Abraham, S. Dash, J. J. P. C. Rodrigues, B. Acharya, & S. K. Pani (Eds.), *AI, Edge and IoT-based Smart Agriculture* (pp. 101–121). Academic Press.

Zeng, C., Zhang, F., & Luo, M. (2022). A deep neural network-based decision support system for intelligent geospatial data analysis in intelligent agriculture system. *Soft Computing*, *26*(20), 10813–10826.

Zhang, P., Guo, Z., Ullah, S., Melagraki, G., Afantitis, A., & Lynch, I. (2021). Nanotechnology and artificial intelligence to enable sustainable and precision agriculture. *Nature Plants*, *7*(7), Article 7.