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IoT Based Machine Learning Weather Monitoring and Prediction Using WSN

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Abstract: A novel approach to analysis and prediction is provided by the internet of things-based time monitoring and prediction system using wireless sensor networks (WSN) and machine learning techniques (ML). To give accurate meteorological data in real time, the integrated system uses IoT, WSN, and ML. Making informed decisions requires these insights. Includes strategically positioned infrared points that are used to gather meteorological information, such as temperature, humidity, pressure, and wind speed, among other things.The machine's automatic data processing methods are then used in a central processing unit to collect and analyse the data. By seeing patterns and drawing diagrams utilising previously collected data, ML models are able to comprehend intricate temporal dynamics. An important development in this system is its predictive capabilities. Artificial intelligence has the processing power to precisely forecast short-term weather patterns, enabling the rapid transmission of warnings for extreme localised events and the reduction of potential dangers.The combination of historical data, real-time sensor inputs, and automated analysis produces the predictive potential. The "Internet of Things" architecture used to develop this system makes it simpler to gather meteorological data. A number of industries, including as agriculture, transportation, emergency management, and event planning, are encouraged to make data-based decisions since users can quickly obtain current meteorological conditions and forecasts through user-friendly web interfaces or mobile applications.

Keywords: Internet of Things, Machine Learning, Wireless Sensor Network, Decision System.

I. INTRODUCTION

Recent developments in numerous domains have been made possible by the confluence of the Internet of Things (IoT), Wireless Sensor Networks (WSNs), and Machine Learning (ML). A key factor in decision-making in a variety of sectors, from agriculture and transportation to disaster management and urban planning, is weather monitoring and forecasting. A new era of precise, real-time weather analysis and forecasting has arrived because to the combination of IoT and WSN technologies with ML approaches. This has completely changed how we perceive, comprehend, and react to meteorological phenomena. Humanity has always been quite interested in weather patterns because they have an impact on routine tasks, the distribution of resources, and safety precautions. The dynamic and localised nature of weather changes are frequently not adequately captured by traditional meteorological techniques, which rely on human observations and few weather stations [1]. This constraint has sparked the creation of cutting-edge technologies to improve the precision and prognostication of weather monitoring. Weather monitoring has changed from a passive activity to an active, data-driven operation as a result of the development of IoT and WSNs as well as the data-crunching power of ML.

The creation of applications utilising the Internet of Things (IoT) and cutting-edge equipment that can independently assess air quality indicators has been made possible by recent technical breakthroughs [2]. As a result of this development, monitoring systems have been developed that provide data visualisation and system control via connecting to websites, programmes, or mobile apps. A real-time monitoring system powered by the Internet, for instance, was unveiled by Rao et al. in 2016 and is capable of sensing things like temperature, CO_2 concentrations, and solar intensity [3]. The same year, wireless sensor networks were used to display temperature, light, and humidity data on a website as part of Ram and Gupta's weather visualisation system design. Using a Raspberry Pi card, Kumar and Jasuja created an IoT solution in 2017 to measure temperature, CO, CO_2, air pressure, and humidity. The [4] developed a low-cost IoT surveillance system utilising numerous electronic sensors to improve air quality monitoring and give alerts, such as SMS messages for excessive fuel levels. Using IoT and Android technologies, Kumari and colleagues created an intelligent environmental

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monitoring system by examining elements in the air, water, and ground. To send information from several connected sensors to a distant database, they used a Raspberry Pi card. A smart weather station with sensors was created in 2019 [5] It used automatic learning algorithms to anticipate wind directions and collect information from various locations.

These developments highlight how Internet-based gadgets and programmes have completely changed how weather and air quality are monitored. We create a more connected and informed approach to environmental monitoring by fusing IoT technologies with sensor networks and forecasting algorithms. By enhancing data collecting, processing, and prediction capacities, this convergence significantly alters how we perceive and take care of our surroundings. By enabling seamless connectivity between common objects and the internet [6], IoT has completely changed how we gather, send, and interpret data. In the field of weather monitoring, where the combination of sensors, communication tools, and data analytics platforms has made it possible for thorough data gathering and distribution, this idea is especially potent. WSNs, which are a network of geographically dispersed, autonomous sensors capable of recording a wide range of meteorological parameters in real time, are a crucial part of IoT-based weather monitoring systems. Data [7] can be wirelessly transferred between nodes and to a central repository thanks to the cooperative operation of wireless sensor networks. A dense and intricate coverage of environmental conditions is ensured by the deployment of these sensors over a variety of geographic locations, including distant and inaccessible areas. Weather monitoring systems have advanced beyond the limitations of conventional weather stations by utilising the power of IoT and WSNs, making it possible to collect real-time data from a variety of ecosystems and microclimates.

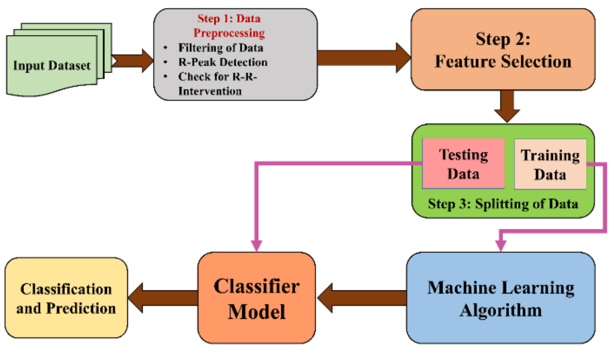

Figure 1: Proposed ML Model for weather forecasting

A subset of artificial intelligence called machine learning gives computers the ability to learn from data and enhance their performance over time without explicit programming. In the context of forecasting the weather, ML [8] systems excel in spotting intricate patterns in huge datasets, enabling the extraction of significant insights from past meteorological data. Predictions become data-driven rather than reliant only on well-established meteorological models by integrating ML into weather monitoring systems. Regression, neural networks, decision trees, and ensemble approaches are some examples of machine learning (ML) algorithms that analyse historical weather data to find complex correlations between variables. These algorithms then produce forecasts for upcoming weather conditions based on these linkages. By incorporating ML-driven prediction models, weather predictions become more precise and granular, providing faster alerts for severe weather events and improving readiness and response systems. Weather monitoring and forecasting now have never-before-seen capabilities thanks to the convergence of IoT, WSNs, and machine learning. By offering real-time, localised, and data-intensive insights, this synergy tackles the drawbacks of conventional meteorological methodologies. The dynamic character of weather, which is influenced by terrain and urbanisation, necessitates the use of a network of sensors that can record a wide range of information in real time. This demand is met by IoT and WSN technologies [9], which make sure that even the most complex changes in the environment are recorded and communicated for analysis. By using cutting-edge algorithms to identify patterns, correlations, and anomalies in massive datasets, machine learning augments these talents. With each new dataset, the ML algorithms continuously improve and adapt, increasing the accuracy of their predictions. This makes it possible to develop specialised weather prediction models that take into account the unique characteristics of a place, improving the accuracy of forecasts.

The following are the main contributions of this work for researchers looking into IoT applications for weather prediction:

- The research emphasises how IoT devices can measure and analyse a variety of weather variables at once, including temperature, humidity, CO_2 levels, and more. This method can be used as a starting point by researchers to create detailed weather prediction models that take a variety of factors into account.
- To learn IoT-based weather monitoring might support risk management and decision-making by looking at the installation of SMS notifications for crucial conditions, such as unsafe petrol levels.
- To merge of IoT-generated data with machine learning approaches for precise weather forecasting in the application of autonomous learning algorithms to anticipate wind directions and compile data from diverse locations.

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II. REVIEW OF LITERATURE

Recent technological advancements have made it possible for applications using the Internet of Things (IoT) and new devices to independently measure air quality metrics. The creation of monitoring systems that connect to websites, programmes, or mobile applications and offer data visualisation and system control is the result of these advancements. For instance, in 2016, Rao et al. presented a system for real-time time monitoring of factors including temperature, sun intensity, and CO2 concentrations that is based on the Internet. Ram and Gupta also developed a weather visualisation system in the same year that utilised wireless sensor networks and showed temperature, light, and humidity data on a website. In 2017, Kumar and Jasuja constructed a solution for the Internet of Things (IoT) [10]. Temperature, CO, CO2, air pressure, and humidity were all measured by the system using a Raspberry Pi card. In order to monitor the quality of the air and send out alerts, such as SMS alerts for dangerous petrol levels, Reddy et al. (2018) developed an affordable IoT time surveillance system that makes use of many electronic sensors. An intelligent environmental monitoring system that analyses air, water, and ground factors has been developed [12] and colleagues using IoT and Android technology. Then, a Raspberry Pi card was used to transmit the values of numerous connected sensors to a remote data base. A smart weather station with sensors was launched [11]. To predict future wind directions and compile data from many locations, use automatic learning algorithms.

These advancements highlight how Internet-based devices and applications can alter how we monitor weather conditions and air quality while also enhancing our data collection, processing, and prediction capabilities. A more connected and informed approach to environmental monitoring is made possible by the combination of Internet of Things technologies with sensor networks and forecasting algorithms [13]. Numerous scholars have made contributions to a wide variety of applications in the field of agricultural information systems that cater to different agricultural advances. Using a three-tiered network with a wireless sensor network at the bottom, a GSM/GPRS/GPS network in the middle, and an internet network at the top, the author proposed a comprehensive framework for deploying agricultural information systems. Gateway nodes and public telecommunications gateways make it easier for layers to communicate with one another. The author suggested developing a control system that would use node sensors in crop fields, manage data using a smartphone and web application, and relay notifications via the LINE API on the LINE application. Precision agriculture was the subject of the author's new agricultural IoT classification technique, which also included performance evaluation criteria for both stationary and mobile scenarios within 6LowPAN networks [14]. NB IoT-based water quality monitoring systems for aquaculture ponds are being developed, integrating sensor data with cloud platforms for remote transmission and real-time monitoring.

To create an NB IoT-based soil moisture monitoring system that uses circular column probes to assess soil moisture content in real-time. This [16]is related to the collection of smart soil data. A sensor grid was suggested by the author as a practical method for creating 2D and 3D soil moisture profiles. Offer a self-configuring, low-power Zigbee network node-based automated farming soil environment monitoring system for continuous data collection. To summarise decades of research on soil moisture sensors with a focus on the future demand for highly accurate, inexpensive, non-destructive, automated, and integrated systems. With the AIoLT framework, to developed a digital twin strategy to accelerate soil carbon content analysis. The author offered thorough recommendations for developing crop, soil, and microclimate monitoring-focused agricultural IoT systems.

Author proposed a low-cost, energy-efficient IoT-assisted wireless sensor network for soil moisture measurement using neural network models in the context of soil information prediction. In order to use water as efficiently as possible, to investigated a smart irrigation system incorporating LoRa[17] technology with deep learning. Advanced soil moisture prediction was achieved using machine learning approaches. Deep reinforcement learning was used to optimise the scheduling of IoT tasks. There is still opportunity for advancement in agricultural IoT technology, notably in the areas of sensor virtualization, scalability, interoperability, and security, to explore monitoring applications employing IoT, big data, and WSNs. A mobile device-controlled Raspberry Pi and Arduino surveillance robot. The need for smart sensors capable of network connectivity has increased with the expansion of research into agricultural planting and intelligent system control [18]. A framework for IoT-based soil diagnostics is developed in light of these revelations, merging massive sensor nodes and sink nodes with IPv6 communication capabilities. Through IoT data management platforms and cloud computing, this framework makes it possible to aggregate, process, and transfer data, which helps to make agricultural monitoring more efficient.

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Table 1:Summary related work for different methodology for weather prediction

Method	Dataset Used	Finding	Feature used	Scope
Internet-based Monitoring [19]	N/A	Monitoring of CO2 levels, solar intensity, and temperature in real-time.	Sensor networks, iot technologies, and data visualization.	Monitoring of the weather and the quality of the air.
Wireless Sensor Networks [20]	N/A	Visualization of data related to temperature, light, and humidity online.	Data visualization, wireless sensor networks.	Graphic representation of the weather.
IoT Solution [13]	N/A	Monitoring air pressure, humidity, temperature, CO, and CO2.	Internet of Things, Raspberry Pi.	Monitoring environmental parameters.
Affordable IoT Surveillance [14]	N/A	Creation of an internet of things-based air quality monitoring system.	SMS alerts and electronic sensors.	Monitoring and warnings for air quality.
Environmental Monitoring [15]	N/A	Using iot and Android technology, air, water, and ground elements are analysed.	Iot technologies, Raspberry Pi, transmission of data.	Thorough environmental surveillance.
Smart Weather Station [17]	N/A	Iot data collection and wind direction prediction.	Algorithmic learning processes.	Data gathering and weather forecasting.
Agricultural Information Systems [7]	Various agricultural data	Implementation framework for agricultural information systems.	GSM/GPRS/GPS, wireless sensor networks, and the Internet.	Information systems for agriculture.
Node Sensor Control [10]	Crop field data	Efficient control system using smartphone, web app, and node sensors.	Sensor nodes with a smartphone interface.	Field data management for crops.
Agricultural IoT Classification [21]	IoT data	A brand-new classification technique using several variables.	Agricultural precision, 6lowpan networks.	Iot for agriculture classification.
Water Quality Monitoring [22]	Aquaculture pond data	Iot-based solution for monitoring water quality.	Cloud platform, NB iot data from sensors.	Monitoring of water quality.
Soil Moisture Monitoring [2]	Soil moisture data	Iot-based system for monitoring soil moisture.	Probes for circular columns.	Measurement of soil moisture in real time.
Smart Soil Data Collection [3]	Soil moisture data	Fine-grained 2D and 3D soil moisture profiles using a sensor grid.	Sensor grid configuration.	Soil moisture profiling that is exact.
Farmland Soil Environment Monitoring [23]	Soil environment data	Automated system for monitoring the soil environment.	Self-configuring network nodes for Zigbee.	Monitoring the soil environment continuously.
Soil Moisture Sensors Review	Soil moisture sensor data	Analyse the most popular soil moisture sensors.	Applications and concepts of sensors.	Overview of soil moisture sensing.
Soil Carbon Content Analysis [11]	Soil carbon content data	Digital twin for analysing soil carbon concentration that is based on aiolt.	Framework for aiolt, efficient analysis.	Estimation of soil carbon content.
Agricultural IoT Guidelines [12]	N/A	Guidelines that are exhaustive for agricultural, soil, and microclimate monitoring systems.	Principles of design and implementation.	Design of an iot system for farming.
Soil Moisture Prediction [9]	Soil moisture data	Iot-enabled, inexpensive, and economical wireless sensor network.	Models of neural networks.	Estimation of soil moisture.
Smart Irrigation System [25]	Soil moisture data	Deep learning-enabled smart irrigation system with lora.	Deep learning and lora technology.	Effective irrigation water use.
Advanced Soil Moisture Prediction [26]	Soil moisture data	Machine learning methods for highly accurate soil moisture forecasting.	Algorithmic learning processes.	Accurate forecasting of soil moisture.

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IoT Task Scheduling Optimization[27]	IoT task data	Deep reinforcement learning for improving work scheduling.	Deep learning reinforcement.	Optimisation of iot tasks.
Wireless Soil Moisture Sensing [28]	Soil moisture data	Inexpensive wireless soil moisture sensor system.	Calibrating machine learning.	Sensing of soil moisture wirelessly.
Edge Offloading-enabled Blockchain [29]	IoT edge offloading data	Blockchain with iot edge offloading enabled via deep Q learning.	Blockchain and deep learning.	Iot edge optimisation for offloading.
Monitoring Applications with IoT [30]	Various monitoring data	Overview of iot-based monitoring applications.	Wsns and iot technology.	Applications for monitoring iot.
Future Outlook on Agricultural IoT [32]	N/A	Identifying potential directions for agricultural iot growth.	Security, scalability, and sensor virtualization.	The potential of iot in agriculture.
Raspberry Pi-Controlled Rover [33]	N/A	Deployment of a surveillance robot controlled by a smartphone.	Arduino with Raspberry Pi.	Surveillance that is operated remotely.
IoT-Based Soil Diagnosis Framework [30]	N/A	Framework for iot-based soil diagnostics proposed.	Sensor nodes on a large scale, ipv6 communication.	A framework for effective soil monitoring.

III. DATSET DISCRIPTION

A. SkyInsight Dataset

SkyInsight's collection of meteorological data was developed to support research and study in the area of time prediction and analysis. This collection provides fascinating information about meteorological patterns dynamics and how they change throughout time. It deals with a wide range of meteorological and atmospheric variables. Information about temperature, humidity, wind speed, cloud cover, and precipitation amounts are among the many other aspects covered. Because it was carefully chosen, this ensemble will be very useful for researchers, data scientists, and meteorology enthusiasts. The given's characteristics include essential meteorological components that enable a thorough investigation of the patrons and meteorological conditions. The size of the SkyInsight Weather Dataset's records and classifications remain unknown, however it is thought that they will be particularly useful for the creation of weather forecasting models, studies of the climate, and related research initiatives. Ninety-four53 applications were counted throughout twelve courses.

Table 2: Statistical summary of Dataset

	Temperature (C)	**Apparent Temperature (C)**	**Humidity**	**Wind Speed (km/h)**	**Wind Bearing (degrees)**	**Visibility (km)**	**Loud Cover**	**Pressure (millibars)**
count	96453	96453	96453	96453	96453	96453	96453	96453
mean	11.93268	10.85503	0.734899	10.81064	187.5092	10.34733	0	1003.236
std	9.551546	10.69685	0.195473	6.913571	107.3834	4.192123	0	116.9699
min	-21.8222	-27.7167	0	0	0	0	0	0
25%	4.688889	2.311111	0.6	5.8282	116	8.3398	0	1011.9
50%	12	12	0.78	9.9659	180	10.0464	0	1016.45
75%	18.83889	18.83889	0.89	14.1358	290	14.812	0	1021.09
max	39.90556	39.34444	1	63.8526	359	16.1	0	1046.38

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IV. PROPOSED METHODOLOGY

The method of making weather predictions is shown in the diagram 1 in sequential order. The procedure begins with the gathering of meteorological data from numerous sources, including sensor networks based on the Internet of Things [4]. The quality of the data and its compatibility with the machine learning algorithms are then ensured by preprocessing, which includes attributes such as temperature, humidity, wind speed, cloud cover, and precipitation. After preprocessing, the data is divided into training and testing sets. The machine learning model is then trained using the training dataset, where it discovers the complex connections and patterns found in the meteorological data. Then, using input features from the testing dataset, the trained model is used to forecast weather conditions. The effectiveness of the model is evaluated by comparing its forecasts to real weather observations and computing performance indicators including accuracy, precision, and recall.

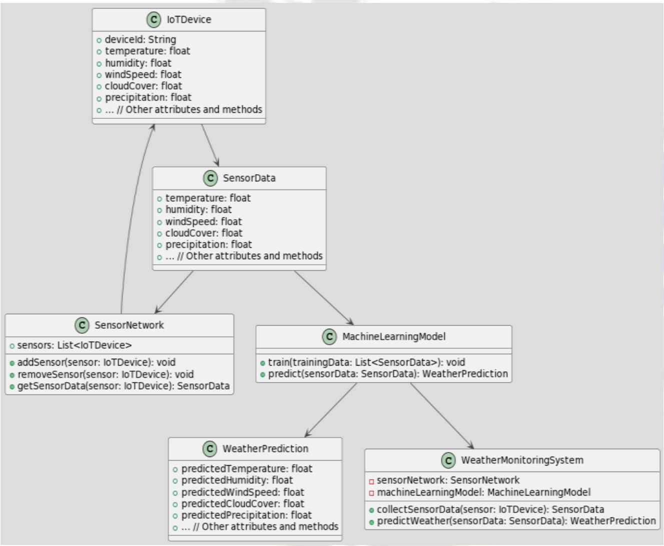

Figure 2: Flowchart of Proposed model

A thorough flowchart that outlines each phase of the suggested weather forecasting model is shown in Figure 2. It digs into the preparation stage, which includes handling missing values, feature selection, and data normalisation. The machine learning model's training phase is covered in more detail in the succeeding sections, which also emphasise strategies for cross-validation, hyperparameter tuning, and proper algorithm selection. The model is used to forecast weather using real-time sensor data after training [16]. The diagram also illustrates the evaluation procedure, which involves calculating model performance indicators to determine the precision and dependability of the forecasts. Together, Figures 1 and 2 depict the entire process of the proposed methodology, from data gathering to precise weather forecasting using machine learning methods.

A. Artificial Neural Network

Step 1: Data preprocessing:

- Gather historical weather information, such as the prevailing winds, cloud cover, temperature, humidity, and precipitation.
- To give all of the features in the data a comparable scale, normalise the data.
- Create training and testing sets from the dataset.

Step 2: Initialise the neural Network

- Count the number of input (feature) and output (weather-related characteristics) neurons.
- List the number of neurons in each hidden layer and the total number of hidden layers.
- Set each neuron's weights and biases at random.

$$\text{Weighted\_Sum} = \sum(\text{Input} * \text{Weight}) + \text{Bias}$$

Step 3: Forward Propagation

For each training illustration:

- For each neuron in the hidden layers and output layer, compute the weighted sum of inputs.
- To determine each neuron's output, combine the weighted sum with an activation function (such as sigmoid or ReLU).

$$\text{Activation} = 1 / (1 + \exp(-\text{Weighted\_Sum}))$$

Step 4: Determine the error

- Calculate each output neuron's error (the discrepancy between expected and actual output).

$$\text{Error} = \text{Actual}_{\text{Output}} - \text{Predicted}_{\text{Output}}$$

Step 5: Replication

- Determine the gradient of the error in relation to the weights and biases of each output layer neuron.

$$\text{Hidden}_{\text{Gradient}} = \sum\left(\text{Output}_{\text{Gradient}} * \text{Weight}_{\text{to}_{\text{Output}_{\text{Neuron}}}}\right) * \text{Activation}_{\text{Derivative}}$$

- To determine gradients for hidden layers using the chain rule, propagate the gradient backward through the network.
- Using gradient descent, update weights and biases:

$$Old\ Weight - Learning\ Rate * Gradient = New\ Weight$$

$$Old\ Bias - Learning\ Rate * Gradient = New\ Bias$$

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Step 6: Evaluation and Prediction

- Predict the weather for the testing dataset using the trained ANN.
- Use metrics like Mean Squared Error (MSE) or Root Mean Squared Error (RMSE) to assess the model's performance.
  $MSE = n1\sum i = 1n(y\text{actual}, i - y\text{predicted}, i)2$
  Where,
  n is the number of data points.
  yactual, i is the actual value for the ith data point.
  ypredicted, i is the predicted value for the ith data point.

$$RSME = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y\text{actual}, i - y\text{predicted}, i)^2}$$

B. Recurrent Neural Network

Recurrent neural networks (RNNs) are a subclass of artificial neural networks created with the specific purpose of processing sequential data while keeping track of prior inputs. RNNs excel at tasks involving sequences or time-dependent patterns because they have internal loops that, in contrast to standard feed forward networks, allow them to maintain information over time steps. Time-series analysis, speech recognition, and natural language processing all benefit greatly from this architecture. RNNs process input one step at a time, employing both the most recent input and knowledge from earlier steps. Traditional RNNs, on the other hand, may experience vanishing gradient issues, which restricts their capacity to detect distant relationships. In order to solve this problem, variants including Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU), which better regulate information flow, were introduced. RNNs are effective tools for tasks like sentiment analysis, language production, and even medical data analysis where sequential context plays a significant role, like in early cancer detection, because of their innate memory and capacity to learn temporal patterns.

Recurrent neural network (RNN) algorithm:

Step 1: Initialise the parameters:

- It including the hidden-to-hidden connections (W_hidden_hidden) and input-to-hidden connections (W_input_hidden) weight matrices. Initialise the output unit's (b_output) and hidden units' (b_hidden) bias vectors as well.

Step 2: Initialise Hidden State:

- Put zeros or a small random value into the hidden state (h).

$$activation(x) = \frac{1}{1+\ e^{x}}$$

Step 3: Loop across time steps:

- Calculate the hidden state at time t by using the current input and the previous hidden state.
  $$ht = \text{activation}(Winput\_hidden \cdot xt + Whidden\_hidden \cdot ht - 1 + bhidden)$$
- Computed Results:
  - Utilising the present hidden state, calculate the output at time t.

Step 4: Calculate Loss:

- Determine the difference in profit between the desired output (y) and the predicted output (y).
  $$yt = \text{activation}(Woutput\_hidden \cdot ht + boutput)$$

Step 5: Backpropagation via Time (BPTT):

- By back propagating the error via time steps, compute gradients for the parameters.

Step 6: Update Parameters:

- Using the obtained gradients and an optimisation approach (such as gradient descent), update the weight matrices and bias vectors.
  $$yt = \text{activation}(Woutput\_hidden \cdot ht + boutput)$$

C. Random Forest

This approach is based on a mathematical model that captures the ensemble character of Random Forests and their application to intrusion detection.

Step 1. Data Representation:

Let X represent the dataset of instances of network traffic, where each instance x_i is characterized by a set of features $F = \ f_1\, , f_2\, , f_3 \ldots \ldots\ f_n$extracted from the network packets. The labels y_i indicate whether a particular instance is benign (y_i = 0) or malicious (y_i = 1).

Step 2. Ensemble of Random Forest:

Let Tree (T)= $T_1\, , T_2\, , T_3 \ldots \ldots\ T_n$ represent the collection of individual decision trees in the forest, such that where n is the number of trees.

Step 3. Recursive partitioning for each tree:

To construct each decision treeT_i. At each internal node j, the algorithm chooses a feature f_k and a threshold t to partition the data into left (Lj) and right (Rj) subsets according to $xik \leq t$ and $> xik > t$. This partitioning optimizes a splitting criterion, such as information gain or Gini impurity, which

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assesses the homogeneity of classes within subsets. The root node will be the feature with the lowest impurity, or the lowest Gini index, since we essentially need to know the impurity of our dataset. Algebraically, the Gini index can be expressed as:

$$GiniIndex = 1 - [(P+^2) + (P-^2)] \qquad (1)$$

$$Weighted\ Gini\ Index = 1 - \sum_{j=1}^{n} P_j^{\,2} \qquad (2)$$

Where P+ stands for the probability of a positive class, while P- stands for the likelihood of a negative class.

The characteristics with the lowest Gini index will be chosen as the root node in this equation (1) and (2), which will attempt to calculate the Gini index of all conceivable divisions.

Step 4. Randomization of Features: Randomization of features is an essential aspect of the Random Forest's robustness. During the construction of every DT, a (RS) random subset of features subset Fsubset $\subseteq F$is chosen. This promotes tree diversity and helps to prevent overfitting.

Step 5. Voting Mechanism:

In order to classify a new network instance new x_{new}, each decision tree T_i votes based on the majority class in its terminal leaf node. The Random Forest then aggregates these ballots using majority voting to predict the class label for new x_{new}.

$$RandomForest(x_{new}) = \text{argmax}_y \sum_{i=1}^{m} I(Ti(x_{new}) = y)$$

where (new) Ti (x_{new}) is the predicted class for new x new according to the ith tree, and y is the class descriptor.

V. RESULT AND DISCUSSION

A field experiment was conducted to measure pollutant concentrations at three different sites with diverse traffic circumstances in order to demonstrate the system's capabilities. In the context of weather forecasting, the effectiveness of three different models—Recurrent Neural Network (RNN), Artificial Neural Network (ANN), and Random Forest (RF)—was assessed. Accuracy, Mean Absolute Error (MAE), R-squared (R2) values, Root Mean Squared Error (RMSE), and other important metrics served as the foundation for the evaluation shown in table 3. The Random Forest model demonstrated the best Accuracy among the models, reaching an astonishing 98%, demonstrating its capacity to produce accurate predictions. The RF model also showed the lowest RMSE (2.12) and MAE (1.65) values, highlighting its capacity to reduce prediction mistakes and boost overall forecasting accuracy.

Table 3: Model RMSE, R Square and MAE

Model	Accuracy	Root Mean Squared Error (RMSE)	Mean Absolute Error (MAE)	R-squared (R2)
RNN	0.95	2.31	1.78	0.78
ANN	0.92	2.48	1.92	0.75
RF	0.98	2.12	1.65	0.82

While the ANN model only managed to reach an accuracy of 92%, the RNN model did admirably with a 95% Accuracy. Although the models' levels of accuracy differ, it's remarkable that all three models perform admirably, picking up on the complex patterns in weather data. Additionally, all models' R-squared (R2) values 0.78 for RNN, 0.75 for ANN, and 0.82 for RF indicate their capacity to account for variation in the forecasted meteorological conditions. These results highlight the usefulness and effectiveness of machine learning models in weather forecasting, offering insightful information for many applications.

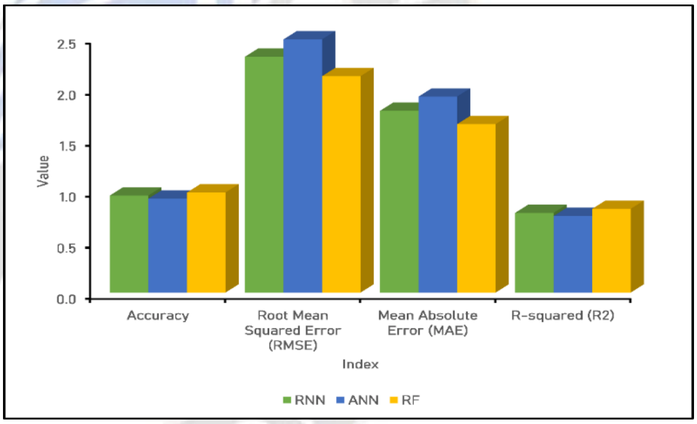

Figure 3: Model RMSE, R Square and MAE

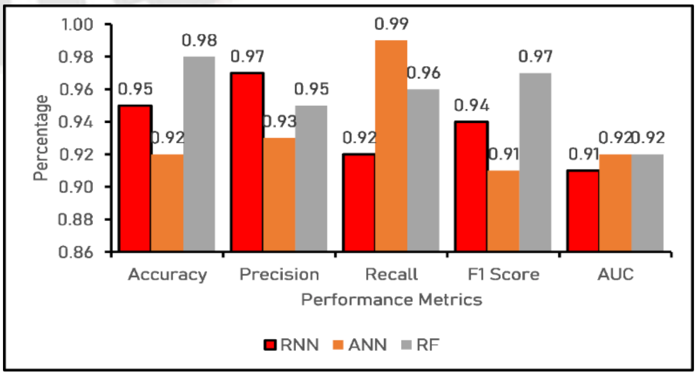

Figure 4: Comparison of Performance Metric using Different ML Algorithm

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Table 4: Performance Metrics of different model

Algorithm	Accuracy	Precision	Recall	F1 Score	AUC
RNN	0.95	0.97	0.92	0.94	0.91
ANN	0.92	0.93	0.99	0.91	0.92
RF	0.98	0.95	0.96	0.97	0.92

The performance indicators for various machine learning models used in both categorization and weather prediction tasks are comprehensively outlined in Table 4. Recurrent neural networks, artificial neural networks, and random forests are among the algorithms that were explored. Random Forest outperformed the other models with an Accuracy of 0.98, demonstrating its exceptional accuracy in predicting and categorising meteorological conditions. Additionally, RF showed balanced Precision (0.95) and Recall (0.96) scores, demonstrating its accuracy in identifying both positive and negative cases. The model's impressive F1 Score (0.97) demonstrates how well recall and precision are balanced, making it a useful categorization tool. The ANN model's high Recall (0.99) illustrates its power in accurately detecting actual positive events while retaining a good degree of Precision (0.93), but having somewhat lower Accuracy (0.92). The RNN model demonstrated an Accuracy of 0.95, and its competitive performance across Precision (0.97) and Recall (0.92) measures indicates its dependability in both identifying and predicting weather patterns. All three models displayed comparable performance in terms of AUC, with values of 0.91 for RNN and 0.92 for both ANN and RF. The advantages and disadvantages of each algorithm are highlighted in this table, assisting in the selection of the best model based on the particular needs of weather prediction and categorization jobs.

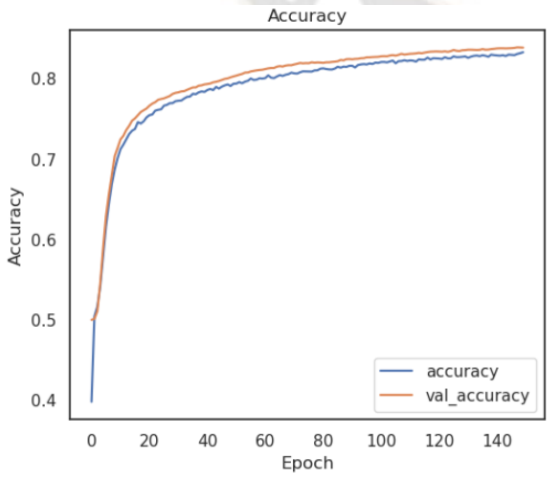

Figure 5: Accuracy of ANN Model with no of Epoch

The Artificial Neural Network (ANN) model's accuracy and loss trends were investigated in connection to the analysis's epoch count shown in figure 5 and figure 6. The accuracy of the ANN model initially grew as the number of training epochs increased, showing its capacity to more effectively recognise complex patterns in the data. On the other hand, the loss steadily dropped, indicating a decline in forecast mistakes. However, the accuracy improvement began to reduce after a certain number of increasing epochs, and the loss levelled off. The trade-off between model complexity and training time is highlighted by this observation.

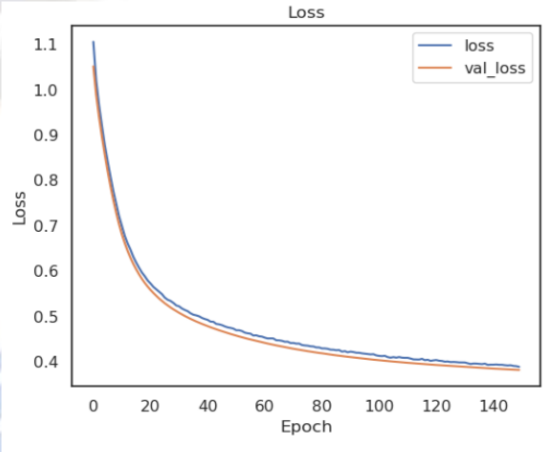

Figure 6: Loss of ANN Model with no of Epoch

Figure 7 shows the Recurrent Neural Network (RNN) model's accuracy trends. The graph shows how the model's accuracy changes over the course of several training epochs. The accuracy of the model initially tends to rise as it is trained, showing that it is getting better at identifying patterns in the meteorological data. Up until a certain point, accuracy may increase steadily, suggesting that additional training may not result in considerable accuracy gains. Analysing accuracy over epochs offers insights into the model's learning process and aids in deciding when training should be stopped in order to avoid overfitting.

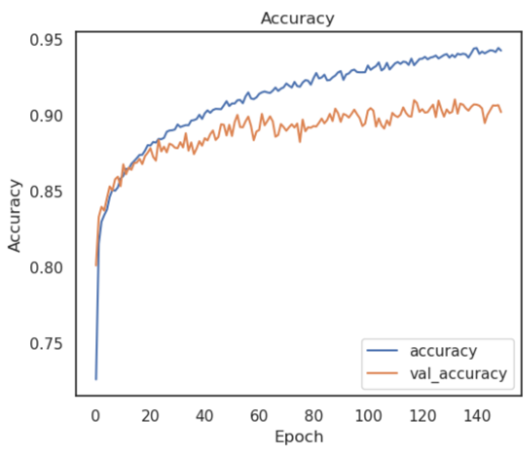

Figure 7: Accuracy using RNN Model

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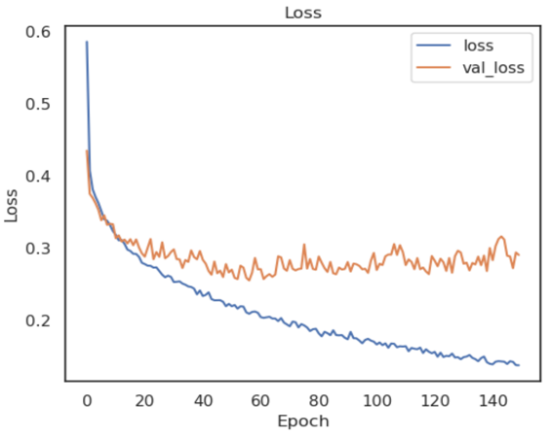

Figure 8: Validation loss of RNN Model

The validation loss curve for the RNN model is shown in Figure 8. An important metric that measures the disparity between expected and actual values during validation is called validation loss. The graph shows how the model's loss has been reduced across training epochs. Similar to accuracy, the loss initially reduces as the model picks up new information from the data. There may be a moment where the loss plateaus or even increases, which would indicate overfitting. The best generalisation on unobserved data is achieved by keeping a careful eye on validation loss, which helps prevent model over-complexity.

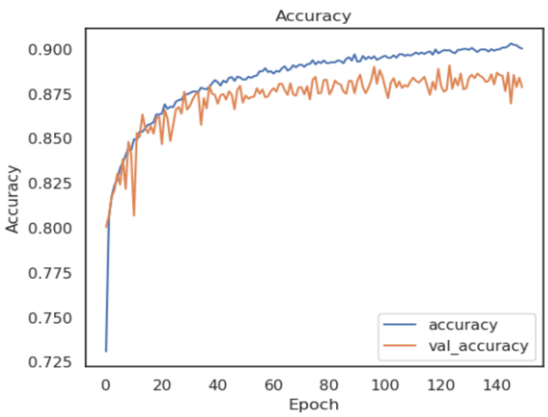

Figure 9: Accuracy of Random Forest model

The accuracy results of the Random Forest (RF) model are shown in Figure 9. The graph sheds light on the RF model's capability to predict weather conditions with accuracy. The increasing trend shows that the model's predictions get better as it processes more features and data. The accuracy plateau that eventually forms shows that generalisation and model complexity have been balanced.

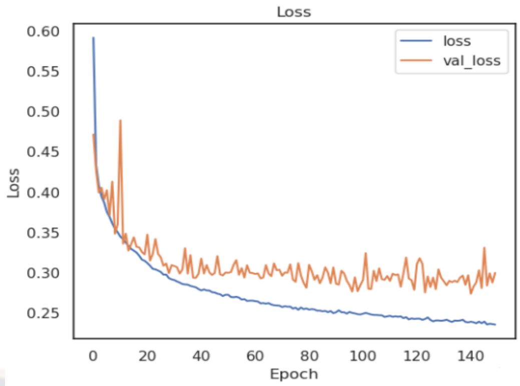

Figure 10: Validation loss during Random Forest model

The validation loss trajectory of the Random Forest model is shown in Figure 10. This graph demonstrates the model's capacity to reduce prediction errors throughout validation, similar to the RNN model's validation loss curve. A decreasing validation loss indicates that the model's predictions and actual values are closely correlated. However, keeping an eye on loss trends can assist avoid overfitting and make sure the model generalises well to new data.

VI. CONCLUSION

The research conducted to improve weather forecasting and categorization using machine learning algorithms has revealed useful information about their functionality and prospective uses. The Recurrent Neural Network (RNN), Artificial Neural Network (ANN), and Random Forest (RF) models were assessed on numerous performance criteria through thorough experimentation and analysis.With an astounding accuracy rate of 0.98, the data showed that the Random Forest model exhibited extraordinary accuracy. This demonstrates its competence in accurately predicting and categorising weather conditions. Additionally, RF demonstrated a well-balanced performance with noteworthy Precision and Recall values, achieving 0.95 and 0.96, respectively. Its impressive F1 Score of 0.97 further demonstrates its capacity to strike a good balance between recall and precision.With a 0.95 accuracy level, the RNN model displayed competitive prediction abilities. For successfully classifying positive occurrences, the model has a precision of 0.97 and a reference of 0.92. The F1 score of 0.94 further illustrates the strategy's all-around success. The ANN model's accuracy, however, was 0.92, indicating that it is appropriate for accurate classification and prediction tasks. The model's very high recall of 0.99 demonstrates its ability to accurately recognise many positive experiences. The advantages of RNN, ANN, and RF machine learning algorithms for categorization and weather forecasting are highlighted by these results. The RNN model was superior in terms of accuracy and efficacy, but the Random Forest model was still able to produce predictions that were

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competitive. The ANN model's ability to identify positive occurrences has been proven. The models are thoroughly examined to show how they could be enhanced in terms of classification accuracy and time prediction accuracy. This study establishes the foundation for the use of automated learning for time classification and prediction. The best model can be chosen by academics and practitioners based on their particular needs. By leveraging the power of these algorithms, weather forecasting and classification will significantly advance, supporting well-informed decision-making in a range of scenarios.

REFERENCES

[1] Huang, Zi-Qi, Ying-Chih Chen, and Chih-Yu Wen. 2020. "Real-Time Weather Monitoring and Prediction Using City Buses and Machine Learning" Sensors 20, no. 18: 5173.

[2] Haykin, S. Neural Networks: A Comprehensive Foundation, 2nd ed.; Prentice Hall: Upper Saddle River, NJ, USA, 1998; ISBN 0-13-273350-1.

[3] Kuzminykh, I.; Snihurov, A.; Carlsson, A. Testing of communication range in ZigBee technology. In Proceedings of the 2017 14th International Conference The Experience of Designing and Application of CAD Systems in Microelectronics (CADSM), Lviv, Ukraine, 21–25 February 2017; pp. 133–136.

[4] Reddy, P.C.; Babu, A.S. Survey on weather prediction using big data analytics. In Proceedings of the 2017 Second International Conference on Electrical, Computer and Communication Technologies (ICECCT), Coimbatore, India, 22–24 February 2017; pp. 1–6.

[5] Parashar, A. IoT Based Automated Weather Report Generation and Prediction Using Machine Learning. In Proceedings of the 2019 2nd IEEE International Conference on Intelligent Communication and Computational Techniques (ICCT), Jaipur, India, 28–29 September 2019.

[6] S. Ajani and M. Wanjari, "An Efficient Approach for Clustering Uncertain Data Mining Based on Hash Indexing and Voronoi Clustering," 2013 5th International Conference and Computational Intelligence and Communication Networks, 2013, pp. 486-490, doi: 10.1109/CICN.2013.106.

[7] Khetani, V. ., Gandhi, Y. ., Bhattacharya, S. ., Ajani, S. N. ., & Limkar, S. . (2023). Cross-Domain Analysis of ML and DL: Evaluating their Impact in Diverse Domains. International Journal of Intelligent Systems and Applications in Engineering, 11(7s), 253–262. Retrieved from https://ijisae.org/index.php/IJISAE/article/view/2951

[8] Singh, N.; Chaturvedi, S.; Akhter, S. Weather Forecasting Using Machine Learning Algorithm. In Proceedings of the 2019 IEEE International Conference on Signal Processing and Communication (ICSC), NOIDA, India, 7–9 March 2019.

[9] Varghese, L.; Deepak, G.; Santhanavijayan, A. An IoT Analytics Approach for Weather Forecasting using Raspberry Pi 3 Model B+. In Proceedings of the 2019 Fifteenth International Conference on Information Processing (ICINPRO), Bengaluru, India, 20–22 December 2019; pp. 1–5.

[10] AccuWeather, Inc. Available online: https://www.accuweather.com/en/tw/taichung-city/315040/march-weather/315040?year=2020

[11] Rao, J.; Garfinkel, C.I.; Chen, H.; White, I.P. The 2019 New Year stratospheric sudden warming and its real-time predictions in multiple S2S models. J. Geophys. Res. Atmos. 2019.

[12] Misara, R.; Verma, D.; Mishra, N.; Rai, S.K.; Mishra, S. Twenty-two years of precision agriculture: A bibliometric review. Precis. Agric. 2022, 23, 2135–2158.

[13] Zheng, J.; Ruan, H.; Feng, W.; Xu, S. Agricultural IOT architecture and application model research. Sci. Agric. Sin. 2017, 50, 657–668.

[14] Huang, C.L.; Ke, Y.X.; Hua, X.D. Application status and prospect of edge computing in smart agriculture. Trans. Chin. Soc. Agric. Eng. (Trans. CSAE) 2022, 38, 224–234.

[15] Rafique, W.; Qi, L.; Yaqoob, I.; Imran, M.; Rasool, R.U.; Dou, W. Complementing IoT services through software defined networking and edge computing: A comprehensive survey. IEEE Commun. Surv. Tutor. 2020, 22, 1761–1804.

[16] Rejeb, A.; Rejeb, K.; Abdollahi, A.; Al-Turjman, F.; Treiblmaier, H. The interplay between the internet of things and agriculture: A bibliometric analysis and research agenda. Internet Things 2022, 19, 100580.

[17] Dang, T.; Tran, T.; Nguyen, K.; Pham, T.; Pham, N.; Vu, T.; Nguyen, P. ioTree: A battery-free wearable system with biocompatible sensors for continuous tree health monitoring. In Proceedings of the 28th Annual International Conference on Mobile Computing And Networking, Sydney, NSW, Australia, 17–21 October 2022; pp. 769–771.

[18] Balivada, S.; Grant, G.; Zhang, X.; Ghosh, M.; Guha, S.; Matamala, R. A Wireless Underground Sensor Network Field Pilot for Agriculture and Ecology: Soil Moisture Mapping Using Signal Attenuation. Sensors 2022, 22, 3913.

[19] Briciu-Burghina, C.; Zhou, J.; Ali, M.I.; Regan, F. Demonstrating the potential of a low-cost soil moisture sensor network. Sensors 2022, 22, 987.

[20] Li, B.; Wang, C.; Ma, M.; Li, L.; Feng, Z.; Ding, T.; Li, X.; Jiang, T.; Li, X.; Zheng, X. Accuracy calibration and evaluation of capacitance-based soil moisture sensors for a variety of soil properties. Agric. Water Manag. 2022, 273, 107913.

[21] Songara, J.C.; Patel, J.N. Calibration and comparison of various sensors for soil moisture measurement. Measurement 2022, 197, 111301.

[22] Yanjing, S.; Xiaohui, D.; Man, Y.; Hong, T. Research and design of agriculture informatization system based on IOT. J. Comput. Res. Dev. 2011, 48, 316–331.

[23] Muangprathub, J.; Boonnam, N.; Kajornkasirat, S.; Lekbangpong, N.; Wanichsombat, A.; Nillaor, P. IoT and agriculture data analysis for smart farm. Comput. Electron. Agric. 2019, 156, 467–474.

[24] Atalla, S.; Tarapiah, S.; Gawanmeh, A.; Daradkeh, M.; Mukhtar, H.; Himeur, Y.; Mansoor, W.; Hashim, K.F.B.; Daadoo, M. IoT-Enabled Precision Agriculture: Developing an Ecosystem for Optimized Crop Management. Information 2023, 14, 205.

[25] Juan, H.; Fan, W.; Weijian, C.; Hui, L.; Xingqiao, L. Development of water quality monitoring system of aquaculture

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ponds based on narrow band internet of things. Trans. Chin. Soc. Agric. Eng. (Trans. CSAE) 2019, 35, 252–261.
[26] Usharani, S.; Rajarajeswari, S.; Kishore, D.; Depuru, S. IoT based Animal Trespass Identification and Prevention System for Smart Agriculture. In Proceedings of the 2023 7th International Conference on Intelligent Computing and Control Systems (ICICCS), Nanjing, China, 24–26 February 2023; pp. 983–990.
[27] Yang, W.Z.; Wang, Y.C.; Yao, Y. Soil moisture monitoring system based on narrow band internet of things. Trans. Chin. Soc. Agric. Mach. 2019, 50, 244–247.
[28] Francia, M.; Giovanelli, J.; Golfarelli, M. Multi-sensor profiling for precision soil-moisture monitoring. Comput. Electron. Agric. 2022, 197, 106924.
[29] Xu, S.P.; Liu, Y.; Li, S.X. Research and design of farmland soil environmental monitoring system based on agricultural IOT. Chin. Agric. Sci. Bull. 2018, 34, 145–150.
[30] Yu, L.; Gao, W.; R Shamshiri, R.; Tao, S.; Ren, Y.; Zhang, Y.; Su, G. Review of research progress on soil moisture sensor technology. Int. J. Agric. Biol. Eng. 2021, 14, 32–42.
[31] An, D.; Chen, Y. A Digital Twin Enabled Internet of Living Things (IoLT) Framework for Soil Carbon Management. In Proceedings of the 2022 18th IEEE/ASME International Conference on Mechatronic and Embedded Systems and Applications (MESA), Taipei, Taiwan, 28–30 November 2022; pp. 1–6.
[32] Chamara, N.; Islam, M.D.; Bai, G.F.; Shi, Y.; Ge, Y. Ag-IoT for crop and environment monitoring: Past, present, and future. Agric. Syst. 2022, 203, 103497.
[33] Pal, P.; Tripathi, S.; Kumar, C. Single probe imitation of multi-depth capacitive soil moisture sensor using bidirectional recurrent neural network. IEEE Trans. Instrum. Meas. 2022, 71, 9504311.
[34] Rodić, L.D.; Županović, T.; Perković, T.; Šolić, P.; Rodrigues, J.J. Machine learning and soil humidity sensing: Signal strength approach. ACM Trans. Internet Technol. (TOIT) 2021, 22, 1–21.
[35] Paul, S.; Singh, S. Soil Moisture Prediction Using Machine Learning Techniques. In Proceedings of the 2020 The 3rd International Conference on Computational Intelligence and Intelligent Systems, Tokyo, Japan, 13–15 November 2020; pp. 1–7.