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PREDICTING GERM DEVELOPMENT CONDITIONS ON CROPS USING REAL-TIME IOT DATA AND ANN MODEL

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ABSTRACT

The prediction of germ development conditions on crops is critical in optimizing crop yields and ensuring sustainable agriculture. This study presents a MATLAB-based artificial neural network (ANN) model for predicting germ development conditions in crops using IoT-based weather data. The research utilizes feedforward neural networks (FNN) algorithms for training, leveraging historical pattern-based weather data collected from IoT sensors for temperature, humidity, moisture, and light intensity (LDR).
The IoT system provides real-time data streams, enabling the ANN models to predict optimal conditions for germ development with high accuracy. The FNN model learns complex relationships between environmental factors and germ development. The proposed system achieves robust performance in scenarios with varying weather conditions, making it a reliable tool for farmers and agricultural planners.
The results demonstrate the feasibility of using IoT-enabled systems and ANN models for agricultural applications, showing significant potential for scalability and integration into smart farming systems.

Keywords: Internet of Things (Iot), MATLAB, Artificial Neural Network (ANN), Feedforward Neural Networks (FNN), Environmental Sensors, Modern Agriculture Etc

1. INTRODUCTION

The prediction of germ development conditions on crops is a cornerstone of modern agriculture, playing a crucial role in optimizing crop production and ensuring food security. Germ development is the primary step of crop diseases which is influenced by a variety of environmental factors, such as temperature, soil moisture, light intensity, and humidity. These factors are dynamic and interdependent, making it challenging to predict germ development conditions accurately without advanced tools. The integration of technology into agriculture, particularly through artificial intelligence (AI) and the Internet of Things (IoT), has created new opportunities for addressing these challenges. This study focuses on utilizing MATLAB-based artificial neural network (ANN) models to predict germ development conditions using IoT-enabled weather data.

Traditional methods of predicting germ development conditions rely on static data and general assumptions about environmental factors. While these methods have been effective to some extent, they lack the precision and adaptability required in modern agricultural systems. Climate variability, regional differences in soil properties, and other local factors necessitate a more sophisticated approach. Predictive models powered by AI can dynamically analyze environmental data, identify complex patterns, and provide actionable insights, enabling farmers to make informed decisions.

ANN models, particularly feedforward neural networks (FNNs), are highly effective in handling nonlinear relationships and learning from complex datasets. When coupled with IoT-based data collection systems, these models can utilize real-time, high-resolution data, enhancing their predictive accuracy. This integration of IoT and ANN technologies has the potential to transform traditional farming practices into data-driven, precision agriculture systems.

2. LITERATURE REVIEW

Agni Biswas and Sarthak Prakash [1] presented a research titled as "Farming Technology for India Agriculture Based Sensorics and Indicative Systems"; This paper aims to introduce methods that offer farmers a practical tool to enhance their knowledge, ultimately leading to improved farm productivity. The approach involves observing parameters such as soil moisture, pH levels, humidity, and soil temperature. Based on the readings from these variables, the system controls the pipe valve by automatically turning it on or off. Upon reviewing this study, it becomes evident that swift technological progress, combined with timely policy measures, has not only prevented a food crisis in India but has also contributed to a consistent rise in agricultural output [1].

Chetan Dwarkani M et al [2] presented the "Smart Farming System Using Sensors for Agricultural Task Automation", In this paper, the author explores the concept of advanced farming by integrating a smart sensing system with an intelligent irrigation setup using wireless communication technology. The system monitors crucial physical parameters such as soil moisture, nutrient levels, and soil pH, all of which significantly impact agricultural operations. By detecting these essential soil characteristics, the system delivers the appropriate amount of green manure, compost, and water to the crops through a smart irrigation mechanism. The study highlights that the irrigation system disperses an adequate quantity of water based on the readings from the moisture sensor [2].

The authors employed an antimony electrode to measure soil pH levels. They investigated the connection between soil resistivity and moisture content, establishing a correlation to evaluate soil moisture accurately. For temperature monitoring, a DS18B20 sensor utilizing the Dallas single-wire protocol was implemented. The system includes Bluetooth technology to transmit collected data to nearby mobile devices. Developed on the STM32Nucleo platform, the setup enables the measurement of soil pH, temperature, and moisture. Communication between the system and the farmer's smartphone is facilitated through Bluetooth, with the entire system running on an STM32 board [3].

P.Sukumar [4] published "Real-time soil fertility analyzer using IoT", where Conventional methods of testing soil fertility in agriculture have been replaced by automated remote monitoring technologies. This advancement allows farmers to gain real-time insights into the current fertility levels of their soil. Soil quality is evaluated by detecting and quantifying various soil elements. For instance, repeated testing has been conducted using electrochemical sensors specifically designed to measure NPK (nitrogen, phosphorus, and potassium) levels in the soil [4].

P. Sindhu and G. Indirani [5] published the "IoT Enabled Soil Testing", the core element of this project system is a microcontroller, specifically the Node MCU equipped with an ESP8266 WiFi module. The setup utilizes various sensors, including those for temperature, soil moisture, and light intensity. This proposed system is both economical and user-friendly. Sensor data is gathered through the NodeMCU and uploaded to a server, where it is used to generate graphical representations. The system offers versatility by allowing integration with other devices, such as water pumps, which can be remotely controlled via a smartphone with internet access. The data is reliably stored and can be accessed from any location. Experimental results and system design confirm that this is a comprehensive solution for assessing soil health parameters. Users can remotely monitor the data and identify any anomalies related to pH levels or soil moisture [5].

Hridesh Shah [6] " IoT Based Soil Testing suggested that, The Internet of Things (IoT) refers to a network of interconnected devices that communicate and exchange data wirelessly over the internet. In this context, the devices include sensors that measure soil moisture, humidity, temperature, and pH levels. IoT technology enhances portability and ensures global accessibility of these devices. With the rapid expansion of internet connectivity worldwide, data can now be transmitted across the globe within seconds, opening up vast opportunities to improve and innovate agricultural practices. This system offers farmers a simple and effective way to analyze soil samples. Once the soil is tested, the sensors gather data and transmit it to a central database. The system then compares this information with stored crop requirements and identifies which crops are best suited for the given soil conditions. Designed to be cost-effective, efficient, and easily transportable, the system can be shared among multiple farmers, making it a practical solution for widespread agricultural use [6].

Anandkumar Vellaichamy [7] "IoT based soil analysis and irrigation system" analyses that the agricultural field is evaluated using three primary parameters. First, soil water content is measured, which plays a crucial role in controlling the operation of the irrigation motor. A soil moisture sensor is able to decide the amount of water present in the soil. Additionally, potential threats like sudden fires that can harm crops and farmland are taken into account. To detect such hazards, a smoke sensor is employed; in the event of a fire, the concentration of gas molecules increases, causing the sensor readings to rise significantly. A temperature sensor is also placed in the field to monitor ambient temperature, providing valuable information to the farmer. This temperature data helps the farmer make informed decisions about whether irrigation is necessary [7].

3. IOT IN AGRICULTURAL APPLICATIONS

The Internet of Things has emerged as a transformative technology in various industries, including agriculture. IoT systems consist of interconnected devices, such as sensors, actuators, and communication modules, which collect and transmit data to central systems for processing and analysis. In agriculture, IoT sensors can measure key environmental parameters like temperature, humidity, soil moisture, and light intensity with high precision.

These sensors, deployed across fields, provide a continuous stream of data, capturing even minute changes in environmental conditions. The ability to monitor and analyze these conditions in real time is invaluable for predicting germ development outcomes. Furthermore, IoT systems enable remote monitoring and automated data collection, reducing the labor and time required for traditional data gathering methods.

4. ANN MODELS FOR PREDICTIVE ANALYTICS

Artificial Neural Networks (ANNs) are computer simulation motivated by the human brain, proficient in learning from data and making predictions based on learned patterns. ANNs are particularly suited for agricultural applications due to their ability to handle noisy, nonlinear, and high-dimensional data. Feedforward neural networks (FNNs), a type of ANN, are widely used in prediction tasks. FNNs consist of an input layer, one multiple hidden layers and output layer. Every layer holds nodes (neurons) connected by weights, which are modified during training to minimize prediction errors.

In this study, FNNs are implemented in MATLAB, a powerful platform for numerical computing and machine learning. By learning from historical and real-time weather data, the ANN models can accurately predict whether given conditions are favorable for germ development.

5. METHODOLOGY

This section outlines the methodology employed in developing and implementing a germ development condition prediction system. The approach integrates IoT-based data collection, data preprocessing, and artificial neural network (ANN) modeling in MATLAB. The methodology is divided into five main stages: data acquisition, data preprocessing, ANN model design, training and validation, and system deployment.

1) Data Acquisition Using IoT Systems

IoT-enabled sensors are deployed in the agricultural field to collect real-time weather data essential for germ development prediction. The following parameters are measured continuously:

- Temperature: Using digital temperature sensors for precise measurement.
- Humidity: Captured with hygrometers to monitor atmospheric moisture.
- Soil Moisture: Measured using soil moisture probes.
- Light Intensity: Monitored with light-dependent resistors (LDR).

The sensors communicate with a central data aggregation system via wireless communication protocols like Wi-Fi. A microcontroller (Arduino) is used to process and transmit the collected data to a cloud storage platform for centralized access. This setup ensures real-time monitoring and the availability of high-resolution datasets for model training.

2) Data Preprocessing

The collected raw data often contains noise, missing values, and inconsistencies due to sensor errors or communication disruptions. Preprocessing is critical to ensure data quality and improve model performance.

- **Noise Removal:** A moving average filter or median filter is applied to smooth out sudden spikes or dips in sensor readings.
- **Handling Missing Data:** Missing values are imputed using statistical methods such as mean or median imputation, or by interpolating from adjacent time points.
- **Normalization:** Input features (temperature, humidity, soil moisture, and light intensity) are normalized to a common scale, typically [0, 1], to ensure uniform weight adjustments during ANN training.
- **Feature Selection:** Principal Component Analysis (PCA) is optionally employed to reduce dimensionality and retain the most significant features influencing germ development.

The preprocessed data is break into training, validation, and test sets in an 80-10-10 ratio to ensure balanced model evaluation.

3) ANN Model Design

A feedforward neural network (FNN) is designed and implemented in MATLAB. The architecture consists of the following components:

- **Input Layer:** Accepts normalized data from IoT sensors, with each feature (e.g., temperature, humidity) representing an input node.
- **Hidden Layers:** Configured with a sufficient number of neurons to capture complex relationships. The optimal number of layers and neurons is determined experimentally using grid search. Activation functions such as ReLU (Rectified Linear Unit) are used to introduce nonlinearity.
- **Output Layer:** Produces a binary output (suitable/not suitable for germ development) or a probabilistic score indicating germ development likelihood.

The backpropagation algorithm is used for training, where weights are adjusted iteratively to minimize the loss function (e.g., mean squared error). The learning rate and momentum are tuned for optimal performance.

4) Training and Validation

The ANN model is trained on the preprocessed dataset using supervised learning. Key steps include:

- **Forward Pass:** The input data is passed through the network, and predictions are generated at the output layer.
- **Error Computation:** The difference between predicted and true values is calculated using a loss function.
- **Backward Pass:** The backpropagation algorithm computes gradients, which are used to adjust weights and biases in the network.
- **Validation:** During training, the model is evaluated on the validation set to monitor overfitting and ensure generalizability.

The training process is repeated over multiple epochs, with early stopping employed if validation performance plateaus or deteriorates. Parameters such as learning rate, batch size, and the number of epochs is optimized using cross-validation.

5) System Deployment

Once the ANN model achieves satisfactory performance, it is integrated into an IoT-based prediction system. The deployment process involves:

- **Model Integration:** The trained model is embedded into a MATLAB application or a standalone executable for use in the field.
- **Real-Time Prediction:** IoT sensors feed real-time data to the model, which processes the inputs and predicts germ development suitability instantly.
- **User Interface:** A graphical user interface (GUI) is developed to display predictions to farmers in a user-friendly format, highlighting actionable insights.

5.1. PERFORMANCE EVALUATION

The system is evaluated using standard metrics such as accuracy, precision, recall, F1-score, and area under the receiver operating characteristic (ROC) curve. Real-world testing is conducted on multiple datasets to assess the system's robustness under different environmental conditions.

6. RESULTS

Feedforward Neural Network (FNN)

A Feedforward Neural Network (FNN) is one of the basic type of artificial neural networks and is widely used for prediction tasks due to its ability to model complex, nonlinear relationships between inputs and outputs. In an FNN model, data flows in one direction—from the input layer, through one or multiple hidden layers, to the output layer—without cycles or loops.

Key components of an FNN include:

1) **Input Layer:** Accepts the features (e.g., temperature, humidity, soil moisture, and light intensity).
2) **Hidden Layers:** Neurons in these layers capture interactions and relationships among the input features using activation functions (e.g., ReLU or sigmoid).
3) **Output Layer:** Provides the final prediction (e.g., whether germ development conditions are favorable).

For this study, the FNN was implemented in MATLAB to predict germ development conditions based on IoT-enabled weather data. The network was trained using backpropagation, which optimized the weights and biases by minimizing the error between predicted and actual outcomes.

Performance Metrics

The FNN's performance was evaluated using standard metrics: accuracy, precision, recall, F1-score, and total runtime. The results achieved were:

- **Accuracy: 0.94768**

Accuracy measures the proportion of exact predictions (both true positives and true negatives) out of the total predictions. An accuracy of 94.768% demonstrates the model's ability to reliably predict germ development conditions in most cases.

- **Precision: 0.94768**

Precision is the ratio of true positive predictions to the total positive predictions. With a precision of 94.768%, the model exhibits a high level of confidence in its positive predictions, minimizing false positives.

- **Recall: 0.66**

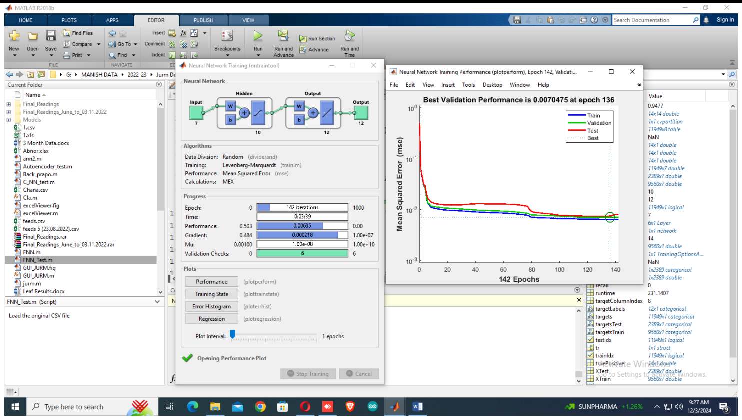
Recall (sensitivity) measures the ability of the model to identify actual positive cases. A recall of 66% indicates that while the model is highly accurate, it misses some true positive cases, possibly due to data imbalance or complex underlying patterns.

- **F1-Score: 0.9870**

The F1-score, the harmonic mean of precision and recall, highlights the balance between these two metrics. With an F1-score of 98.70%, the model is highly effective in handling the trade-off between precision and recall, indicating superior performance overall.

- **Total Runtime: 231.1407 seconds**

The runtime represents the total time required for the training and evaluation of the model. Despite the computational complexity, the runtime of approximately 231 seconds is reasonable for a robust model like an FNN, especially when trained on IoT-generated high-dimensional data.



Screenshot: Performance of Feedforward Neural Network (FNN)

7. CONCLUSION

In this study, one of the methods of ANN i.e. Feedforward Neural Network (FNN) model is developed and evaluated for predicting germ development conditions on crops in an agriculture land using IoT-based weather data.

CONFLICT OF INTERESTS

None.

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