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Real-Time Soil and Plant Monitoring via Optimized WSN and Data Mining for Sustainable Farming

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Abstract—

Sustainable agriculture demands efficient resource utilization and continuous environmental monitoring to maximize crop productivity while minimizing environmental impact. This work presents the implementation of a real-time soil and plant monitoring system using an optimized Wireless Sensor Network (WSN) integrated with data mining techniques. The proposed system continuously monitors critical agricultural parameters such as soil moisture, temperature, pH, and plant health indicators.

By deploying an energy-efficient WSN architecture, the system ensures low power consumption and reliable data transmission from distributed sensors to the central processing unit. Collected sensor data is analyzed using data mining algorithms to extract meaningful patterns, predict crop health, and support decision-making processes for irrigation, fertilization, and pest control. This predictive approach aids farmers in optimizing resource usage, reducing costs, and promoting eco-friendly agricultural practices.

The integration of WSN and data mining in this system provides real-time insights for precision agriculture, improving crop yield while supporting sustainable farming objectives. Experimental results demonstrate the system's effectiveness in monitoring field conditions accurately and making data-driven recommendations for agricultural management.

Keywords—Precision Agriculture, Data Mining,Wireless Sensor Networks (WSN), Internet of Things (IoT), Soil Monitoring, Crop Management, Energy-Efficient Protocols, Smart Irrigation, Nutrient Monitoring, Real-Time Agricultural Monitoring, Sustainable Farming.

I. INTRODUCTION

The rapid growth of global population and food demand has placed significant pressure on agricultural systems to produce higher yields while preserving natural resources. Traditional farming methods often lead to overuse of water, fertilizers, and pesticides, resulting in environmental degradation and reduced soil fertility. To address these challenges, Precision Agriculture (PA) has emerged as a transformation approach, integrating advanced technologies such as Wireless Sensor Networks (WSN) and Data Mining to monitor, analyze, and optimize agricultural processes.

WSNs play a critical role in real-time field monitoring by deploying multiple sensors to collect data on key parameters such as soil moisture, temperature, humidity, and plant health. However, the effectiveness of WSNs is often hindered by limitations in energy consumption, data redundancy, and communication inefficiencies. Therefore, optimizing WSN deployment and operation is essential for ensuring long-term, real-time agricultural monitoring with minimal energy use.

In parallel, data mining techniques enable the extraction of meaningful patterns from large volumes of agricultural data. By applying predictive models and pattern recognition algorithms, farmers can gain insights into crop health, resource requirements, and potential risks, facilitating data-driven decision-making for sustainable farming.

This paper presents the implementation of an optimized WSN combined with data mining for real-time soil and plant monitoring in sustainable agriculture. The proposed system enhances energy efficiency, provides continuous environmental monitoring, and leverages predictive analytic to support precision farming. The objective is to help farmers improve crop productivity while reducing environmental impacts, thereby contributing to long-term agricultural sustainability.

II Literature Review

In recent years, the integration of **Wireless Sensor Networks (WSN)** and **Data Mining** in agriculture has gained significant attention due to their potential to enhance real-time monitoring and decision-making processes.

Several researchers have developed WSN-based systems for agricultural applications. In [1], the authors proposed a WSN framework for monitoring soil moisture and temperature, enabling farmers to make informed irrigation decisions. However, energy efficiency remains a major concern, as sensor nodes have limited battery life and frequent data transmission leads to high power consumption.

In [2], an adaptive routing protocol was introduced to reduce communication overhead in WSNs, prolonging the network lifetime in agricultural monitoring. Although this approach optimizes network operation, it does not address the analysis of collected data for predictive insights.

Data mining techniques have been explored in agriculture for pattern recognition and crop prediction. In [3], classification algorithms were applied to historical agricultural data to forecast crop yields. Similarly, clustering techniques have been used in [4] to segment agricultural fields based on soil characteristics, supporting precision farming decisions. However, most of these studies analyze offline data, limiting their applicability for real-time scenarios.

Some researchers have combined WSN with data analytics to support precision agriculture. In [5], real-time sensor data was processed using machine learning models to detect plant diseases and environmental anomalies. Despite promising results, the system faced scalability issues due to network limitations.

While existing works contribute to advancements in smart farming, there is still a need for an integrated system that combines **optimized WSN deployment with real-time data mining** to enhance both monitoring efficiency and predictive capabilities.

The present work addresses these gaps by proposing an energy-efficient WSN system coupled with data mining algorithms for continuous soil and plant monitoring. This integration provides actionable insights for farmers, promoting **sustainable agriculture** through intelligent decision support.

I. Energy-Efficient Data Collection in WSNs

Longfei Shangguan et al. [1] introduced a study titled "Energy-Efficient Heterogeneous Data Collection in Mobile Wireless Sensor Networks," focusing on optimizing data collection in heterogeneous WSNs. The authors formulated a Rendezvous Planning (RP) problem with realistic assumptions and proposed the RP-ME algorithm, achieving a time complexity of O(n log n). This method optimizes the mobile element (ME) trajectory in a tree-shaped network, ensuring the ME remains close to high data-generating nodes, thus minimizing unnecessary long-distance data transmissions. The approach significantly reduces energy consumption by meeting lower latency requirements.
Sherin Mathew et al. [2] proposed a novel MobiCluster technique for data collection using mobile sinks. This method employs public transport buses for bidirectional data retrieval, enhancing communication, increasing data throughput, and supporting sustainable energy usage. By clustering the network and designating periphery nodes (RNs) for data transmission, the method balances energy consumption and prevents redundant data collection.
Noushin Rakhshan et al. [3] developed a technique to extend the lifespan of WSNs through mobile sink optimization. The method evaluates packet size and node count to optimize the sink's movement, thereby reducing hops and conserving energy. They also proposed a Traveling Salesman-based algorithm to determine the optimal Hamiltonian circuit for the mobile sink during each clustering phase.
Mujdat Soyturk et al. [4] introduced the S-SWR (Stateless Weighted Routing) method, which supports multiple sinks in WSNs. This routing strategy does not require prior topology knowledge, making it scalable for large sensor networks. The primary goal is to optimize energy usage and extend network longevity by distributing traffic evenly without network reconfiguration.
YoungSang Yun et al. [5] presented a mobile sink-based approach designed to maximize WSN lifetime, assuming applications tolerate delayed data delivery. The work compares this method with existing lifetime maximization techniques, providing mathematical models to validate its efficiency.
Z. Wang et al. [6] developed a novel programming model to reposition mobile sinks dynamically using linear programming. This approach ensures uniform energy distribution across the network, significantly extending the lifespan of sensor nodes.
S. Basagni et al. [7] explored controlled sink mobility as a method to prolong WSN lifetime. The study proposed a Mixed Integer Linear Programming (MILP) solution for sink mobility management and introduced a distributed model called GMRE (Generalized Mobility and Resource Evaluation), which determines optimal sink placement and time allocation based on network data demands and processing rates.

II. AI-Powered Plant Monitoring

An AI-powered plant monitoring system has been proposed to detect and classify plant diseases using image processing techniques. The process begins with per-processing of leaf images, where the CIELAB color model is applied to convert RGB images into a format aligned with human color perception. This conversion assists in distinguishing between healthy and diseased regions.
The methodology consists of four main stages:

1. **Initial Processing:** Converts RGB images into the CIELAB color space to facilitate accurate color distinction.
2. **Partitioning**: Segments the image into healthy and diseased areas, isolating the infected regions.
3. **Feature Extraction**: Extracts specific features from the diseased sections to characterize the nature and extent of the infection.
4.**Partitioning:** Segments the image into healthy and diseased areas, isolating the infected regions.
5. **Feature Extraction:** Extracts specific features from the diseased sections to characterize the nature and extent of the infection.
6. **Categorization:** A trained classifier analyzes the extracted features to determine the disease type affecting the plant.

The model is rigorously evaluated using various performance metrics to ensure reliability and accuracy in disease detection. Further methodological details are elaborated in the following sections of the study.

Affected Part Segmentation

This is the next phase in the procedure. The disease-affected part of the input thermal image is segmented in this method. Then it's just a matter of determining the disease's type and severity. The Artificial Bee Colony (ABC) Algorithm is utilised to segment the impacted area. ABC was originally presented by Faudziah Ahmed under the inspiration of collective behaviour of honey bees with better performance in function optimization problem.

Artificial Bee Colony (ABC) Algorithm

The ABC algorithm, inspired by the foraging behavior of honeybees, follows a structured process for optimization. The steps are detailed as follows:

Initialization of Food Sources:
All potential solutions are initialized by generating subsets of the problem space. Each subset represents a food source location, which corresponds to a candidate solution.

Iterative Process:
The algorithm operates in cycles, continuously improving the solutions until a termination condition is met.

Employed Bee Phase:
Each employed bee is sent to a specific food source (solution) to evaluate its nectar amount, which is analogous to calculating the fitness of the solution.

Onlooker Bee Phase:
Based on the fitness information shared by employed bees, the onlooker bees determine the probability

of selecting a particular food source. This probability is computed using a fitness-based selection mechanism.

Exploitation by Onlooker Bees:
Onlooker bees are assigned to the food sources according to the computed probability values. They further examine the quality of the solutions by collecting nectar and assessing the updated fitness values.

Abandonment of Poor Solutions:
Food sources that fail to improve over a specific number of trials are abandoned. This avoids wasting resources on suboptimal solutions.

Scout Bee Phase:
When a food source is abandoned, scout bees randomly explore the search space to discover new potential food sources, ensuring diversity in the population.

Memorization of the Best Solution:
Throughout the process, the best solution found so far is stored and updated until the stopping criteria, such as the maximum number of iterations or acceptable error margin, is satisfied.

Feature Extraction

After the segmentation phase, the next critical step involves the extraction of significant features from the segmented regions. These features play a vital role in the accurate identification and classification of plant diseases. The feature set is carefully designed to capture the distinguishing characteristics of the diseased part, enabling robust and unique disease recognition.

In this study, **three primary categories of features** are extracted:

Texture Features:
Texture information provides insights into the surface pattern and local variations within the segmented region. The Transform Encoded Local Binary Pattern (TELBP) method is employed to extract texture features. TELBP captures the spatial structure and local texture distribution, making it suitable for complex agricultural image analysis.

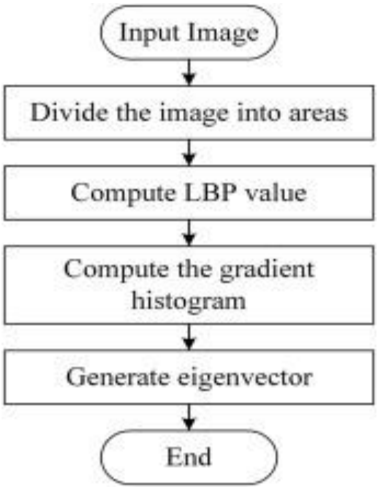
Shape Features:
The shape of the infected region is another important indicator for disease classification. The **Modified Zernike Moment (MZM)** technique is utilized to derive shape descriptors. MZM provides rotational invariance and accurately represents the geometrical structure of the diseased area.

Color Features:
Color attributes are extracted to capture chromatic changes associated with different disease conditions. These features help differentiate diseases that cause discoloration or pigmentation changes in the plant tissue.

The combination of these features—**texture, shape, and color—forms a comprehensive feature set** that enhances the disease classification accuracy in subsequent stages.

Transform Encoded Local Binary Pattern (TELBP)

To extract texture features using TELBP, the flow chart as following steps are applied to each pixel in the image:

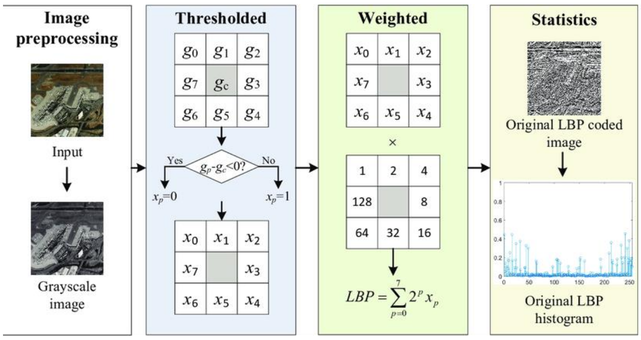


Steps:

We first give a brief review of the original LBP method and its extensions that form the basis for our work. The original LBP, introduced in [25], describes the texture information of a pixel of an image by considering its surrounding elements. For that purpose, LBP method proceeds in three steps. First the eight neighbors in 3 × 3 window size are compared by the value of the considered central pixel

The LBP code for a pixel at coordinates (xc, yc) is calculated as follows:

Code: LBP(xc, yc) = ∑ (s(gp - gc) * 2^p) from p=0 to P-1



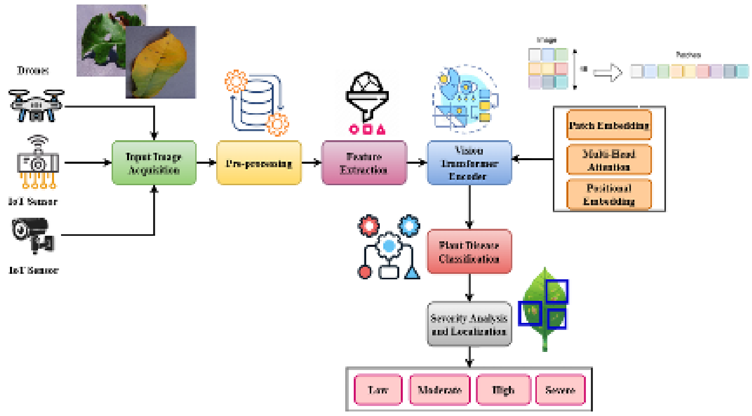
CALCULATION OF THE LOCAL BINARY PATTERN (LBP).

To extract texture features using TELBP, the following steps are applied to each pixel in the image:

1. Identify the surrounding pixels S_p S_c of a center pixel S_c_S_c based on a fixed radial distance PPP.
2. Apply the **Discrete Fourier Transform (DFT)** on both the center pixel and its neighborhood to compute their respective frequency-domain coefficients.
3. Compare the DFT coefficient of the center pixel (DFTCc DFTc DFTCc) with the coefficients of each surrounding pixel (D_F)
4. Assign a binary value of **1** if the center pixel's coefficient is higher than that of its neighbor.

5. Assign **0** in cases where the surrounding pixel's coefficient is equal to or greater than the center pixel's coefficient.
6. Combine the binary outcomes into a single binary number and convert this value to its decimal equivalent.
7. This resulting value is termed the **local binary pattern descriptor** for that pixel.
8. Finally, the descriptors are stored in an array, referred to as **Bin**, representing the texture pattern of the entire image.

Improved Convolutional Neural Network (ICNN) Algorithm


Drones
IoT Sensor
IoT Sensor
Input Image Acquisition
Pre-processing
Feature Extraction
Vision Transformer Encoder
Patch Embedding
Multi-Head Attention
Positional Embedding
Plant Disease Classification
Severity Analysis and Localization
Low
Moderate
High
Severe

1. In Initial stage convolution filter is applied.
2. By subsampling it will reduce the sensitivity of the filter.
3. An activation layer manages of signal transfer from one layer to the next.
4. Using the Rectified Linear Unit, shorten the training period (RELU)
5. Each neuron in the following layer is linked to a neuron in the flow layer.
6. At the end of an offline phase, add a loss layer to provide information to the neural network.

II. SMART SOIL MONITORING

1) *Role of Data Mining in Soil Monitoring*

Data mining involves extracting hidden patterns, correlations, and insights from large datasets. In **soil monitoring**, data mining is used to process and analyze sensor data related to:

1. **Soil Moisture Levels**
2. **Temperature and Humidity**
3. **Soil pH and Nutrient Content**
4. **Salinity and Electrical Conductivity**

By applying data mining techniques, farmers and agronomists can uncover valuable knowledge that supports precise and sustainable land management.

Data Mining Techniques in Soil Monitoring

Classification: Classifies soil conditions (e.g., dry, optimal, over-irrigated) using algorithms like Decision Trees, Support Vector Machines (SVM), or Random Forests. Helps in predicting irrigation needs or identifying unsuitable soil zones.

Clustering: Groups similar soil types or conditions using K-means or DBSCAN algorithms.Useful for field segmentation and site-specific management.

Regression Analysis: Predicts continuous soil parameters such as future moisture levels or nutrient depletion rates. Supports forecasting and proactive farming practices.

Association Rule Mining: Discovers relationships between different soil and environmental factors.

Example: Identifying that low moisture levels frequently coincide with specific temperature ranges.

Anomaly Detection: Detects unusual soil behavior (e.g., sudden pH changes or unexpected dry patches). Assists in early warning systems for plant stress or irrigation system failures.

B. *Data Collection*

Data Collection is the core of any Smart Soil Monitoring System. It involves the systematic gathering of real-time soil information using embedded sensors and wireless communication devices. The collected

data helps in understanding soil conditions, supporting timely agricultural decisions such as irrigation, fertilization, and crop selection.
The data used for this work are obtained for the years from 1965 to 2019. The data are taken in nine input variables. The variables are 'Crop', 'Month', 'Year', Moisture, 'Area of Sowing', 'Humidity', 'Temperature' and 'Production'.

A. **Preliminary Data Processing**

Raw data collected from soil sensors is often prone to noise, missing values, inaccuracies, and outliers due to environmental factors or sensor faults. Pre-processing prepares the data for accurate analysis, ensuring the reliability and efficiency of subsequent decision-making processes in precision agriculture.

B. **Volume-Oriented Feature Identification**

The pre-processed data is given to volumetric approach to predict the yield. Clustering is a fundamental challenge in data mining: grouping a set of items based on a measure of similarity. This deceptively simple premise has spawned a slew of challenges, as well as the techniques to solve them. A number of clustering algorithms are provided by sickest-learn, although they only cover a small portion of the field's diversity. Each of the nxn samples to be grouped is represented by a pxp dimensional feature vector in many clustering applications. A matrix of shape npxnp can then be used to represent the full dataset. Each sample is assigned to one cluster after performing a clustering technique.

III. DATA COLLECTION

The data are extract by the proposed volumetric method. To extract data values, a common soil preparation process known as the volumetric method is applied.Temperature and humidity sensors, in addition to moisture sensors, are helped to keep track of the amount of heat in the greenhouse and the amount of moisture in the air This is accomplished using wireless moisture sensors (WMS), wireless temperature sensors (WTS), and wireless humidity sensors (WHS). Moisture, temperature, and humidity data were collected at one-hour intervals using these sensors.

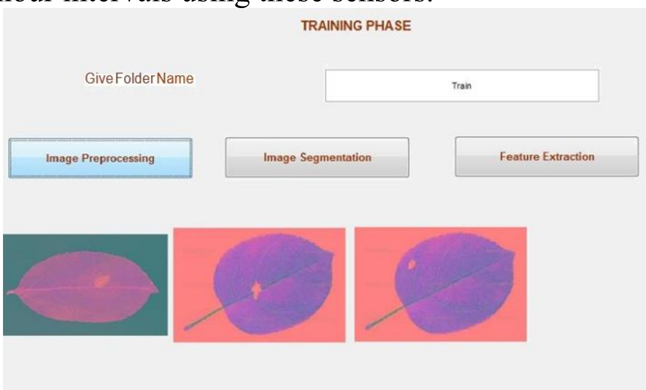


Fig 1. Image Preprocessing

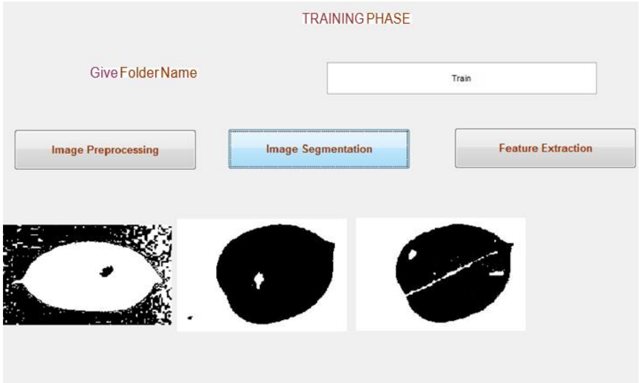


Fig 2. Image Segmentation

SL .No	Training Features Extraction		
	Modified Color Moment	***Modified Zernike Features***	***TLEP Features***
1.	179.949	-0	0.98724
2.	0.875899	0.779362	0.02552
3.	115.636	0.598165	0.84044
4.	137.06	0.611493	0.471838
5.	683.72	-0	0.999607
6.	3415.11	1.23915	0.950728
7.	-1.92092	1.29295	9.04719
8.	1.78872	1.3203	9.04719
9.	10.7287	-0	0.977

SL .No	Training Features Extraction		
	Modified Color Moment	***Modified Zernike Features***	***TLEP Features***
			579
10.	10.6904	1.38843	0.0448413
11.	93.3738	1.51328	0.906188
12.	267072	1.64878	0.454766
13.	2.00301	3.0557e+09	0.99931
14.	14.3955	32944.3	0.913419

Table 1 Trainig Feature Extraction

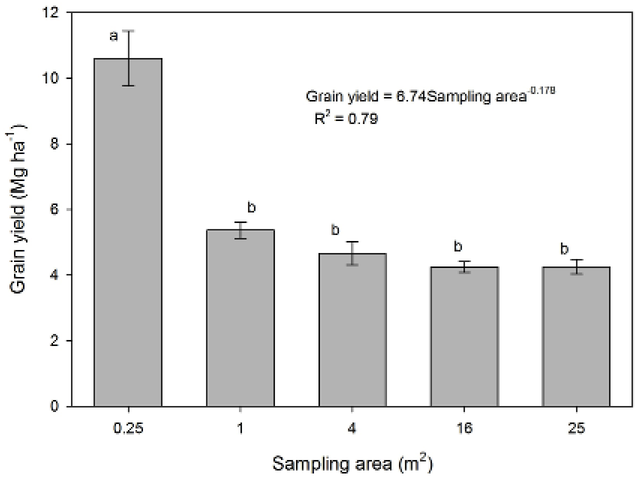


FIG 3 Graph for Soil Monitoring

The feature are used to uniquely identify the disease name. The Fearure extraction has three type of features such as in the Table 1 Texture, Shape and Color. Modified Zernike Moment method is used to extract the shape feature, Modified Zernike Features and TLEP Features. In Smart Soil Monitoring. The data are collect in nine input variables. The variables are 'Crop', 'Month', 'Year', Moisture, 'Area of Sowing', 'Humidity', 'Temperature' and 'Production'. The volumetric method has been used to extracting data values. The collected data are pre--processed before applying the prediction techniques. The pre-processed data is given to volumetric approach to predict the yield. The result for the predict Yield is 592.4 Kilo. When compared with other existing method, the proposed method showed a better result.

IV. Result and Discussion

In smart plant monitoring module, the leaf image is pre-processed. the input leaf image is used for disease detection.To depict disease detection technique is based on the CIELAB conversion. CIELAB color model is applied for pre-processing Fig 1. The source picture is split ed into illness and non-disease regions in the segmentation stage Fig 2. After the non-illness zones have been removed, just the disease regions remain. Multiple characteristics are extracted in the feature extraction process to describe each of the disease regions. After the characteristics have been created, the disease regions are classified using the previously trained classifier model. Finally, using performance measurements, the detection results are checked and analyzed.

V. CONCLUSION

In this work, a Smart Soil and Plant Monitoring System has been successfully developed, integrating real-time data acquisition with a volumetric analysis approach. By characterizing soil conditions, plant health, and environmental factors, the system enables accurate crop yield prediction and supports decision-making for precision agriculture. The proposed method not only enhances agricultural productivity but also promotes sustainable farming practices by minimizing unnecessary resource use and reducing environmental impacts. Overall, the implementation of this system demonstrates a practical and efficient solution that aligns with the goals of smart farming and sustainable agriculture management.

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