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Leveraging Data Exchange and Random Forest Regression Model for Precision Farming: Predicting Soil pH to Enhance Agricultural Efficiency

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Abstract

Precision farming is revolutionizing agriculture by incorporating advanced technologies and data-driven methods to improve crop production. However, a gap persists in the practical use of machine learning (ML) models and real-time data exchange for optimizing soil conditions to enhance crop yields, reduce resource waste, and limit environmental impact. This study aims to bridge this gap by leveraging ML, particularly focusing on soil pH prediction to ensure optimal nutrient absorption for plant health. Data was collected from Kigali Independent University ULK in Gasabo District, Kigali City, Rwanda, using seven soil sensors measuring soil moisture, temperature, humidity, NPK levels, and pH. The study applied a Random Forest regression model to predict soil pH, achieving an impressive accuracy of 99.9%, surpassing several contemporary models. The results highlight the effectiveness of ML in offering valuable insights to farmers, promoting sustainable and profitable agricultural practices. The research emphasizes the importance of continuous technological innovation and collaboration to push the boundaries of modern agriculture

Keywords: Precision Agriculture; Advanced Technologies; Machine Learning; Data-Driven Approaches, Decision-Making Frameworks; Sustainable Farming Practices

1. Introduction

The integration of data exchange and machine learning into precision farming has significantly transformed agricultural practices, enhancing productivity, efficiency, and sustainability(Gyamfi et al., 2024). Precision farming involves managing crops on a micro-scale using detailed field data to optimize agricultural activities(R. K. Singh et al., 2021). Machine learning (ML) plays a pivotal role, analyzing extensive agricultural data to generate actionable insights(Choudhary et al., 2024).

Data exchange is crucial in precision farming as it enables the collection and distribution of information across agricultural platforms(Shukla et al., 2023). This seamless flow of data facilitates real-time monitoring and decision-making, essential for adapting to changing field conditions(Rozenstein et al., 2024). By leveraging ML algorithms, farmers can analyze data from various sources, including satellite imagery, weather forecasts, soil sensors, and crop health monitors(Mohyuddin et al., 2024). These analyses help predict

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crop yields, detect diseases early, and optimize the use of resources like water and fertilizers(Akhter & Sofi, 2022).

Machine learning has a profound impact on precision farming. ML has a profound impact on precision farming by processing complex datasets to identify patterns not immediately evident to humans(Mgendi, 2024). For instance, ML models can predict optimal planting and harvesting times, forecast pest infestations, and recommend precise amounts of inputs, reducing waste and increasing yields(Miles, 2019). ML also drives the development of automated systems for tasks such as irrigation and harvesting, enhancing efficiency and lowering labor costs(Mekonnen et al., 2020). Effective data exchange among stakeholders—including farmers, agronomists, researchers, and technology providers—is indispensable for the success of precision farming in Rwanda(Fluturim & Luqman, 2023). This collaborative approach ensures timely dissemination of relevant information, enriching decision-making and facilitating prompt interventions(Akhter & Sofi, 2022).

Rwanda, with its agricultural traditions and commitment to technological progress, is increasingly adopting precision farming to boost productivity and sustainability(Widtayakornbundit & Luangpituksa, 2023). This approach utilizes state-of-the-art technologies to enhance resource allocation and improve crop yields through precise management practices tailored to local conditions(Kendall et al., 2022). Central to precision farming is the ability to gather, analyze, and interpret extensive datasets (Rika Widianita, 2023)(Miklyaev et al., 2021). Machine learning, as a subset of artificial intelligence, provides advanced analytical capabilities for processing complex data(Condran et al., 2022). In Rwanda, integrating ML empowers farmers to forecast crop performance, detect diseases early, and optimize irrigation and fertilization schedules with precision(Araújo et al., 2023).

Moreover, effective data exchange among stakeholders—including farmers, agronomists, researchers, and technology providers—is indispensable for the success of precision farming in Rwanda(Liakos et al., 2018). This collaborative approach ensures timely dissemination of relevant information, enriching decision-making and facilitating prompt interventions and practices. This study aims to explore the impact of data exchange and ML in precision farming within Rwanda's context(*Research on World Agricultural Economy Comparative Analysis of Machine Learning Models for Predicting Rice Yield : Insights from Agricultural Inputs and Practices in Rwanda*, 2024). By investigating these technological advancements, the study seeks to maximize productivity, promote sustainability, and address unique challenges in Rwanda's agricultural sector(Buheji, 2024). The research contributes to agricultural innovation and economic growth in Rwanda through precision farming technologies(Dimkpa et al., 2023).

The agricultural sector is evolving with advanced technologies to boost productivity and sustainability(Olabimpe Banke Akintuyi, 2024). Precision farming has emerged as a transformative strategy, enhancing resource efficiency and increasing crop yields through meticulous management practices(Tahir, n.d.). This approach harnesses information technology to deliver precisely tailored support to crops and soil(Mohyuddin et al., 2024). Machine learning plays a pivotal role in processing and analyzing extensive datasets

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essential for informed decision-making(Tursunalieva et al., 2024). Machine learning provides sophisticated analytical tools to forecast crop performance, detect pests early, and optimize irrigation and fertilization schedules, among other tasks(Rane et al., n.d.). Effective data exchange facilitates seamless information flow among stakeholders, enhancing decision-making processes(Elbasi et al., 2023). This integration of data from various sources allows accurate analysis and efficient farm management(Mokogwu et al., 2024). It empowers farmers to make proactive decisions, improving crop yields and minimizing environmental impact(Robert et al., 2016). Understanding the impact of data exchange and ML in precision farming is vital for advancing agricultural methodologies(Bhat & Huang, 2021). This study aims to explore how these technologies can be integrated into farming practices to maximize benefits and tackle challenges confronting modern agriculture(Mekonnen et al., 2020). Rwanda, celebrated for its rich agricultural heritage and rapid technological advancements, is increasingly embracing precision farming as a pivotal strategy to boost agricultural productivity and sustainability. This approach utilizes cutting-edge technologies to optimize resource allocation and enhance crop yields through meticulous management practices tailored to local environmental conditions(Khan & Kashem, 2023).

At the core of precision farming lies the ability to collect, analyze, and interpret extensive datasets. Machine learning, a subset of artificial intelligence, plays a critical role in this process by providing advanced analytical capabilities necessary for processing and deciphering complex datasets. In Rwanda, where agriculture serves as a cornerstone of the economy and supports a significant portion of the population, integrating machine learning empowers farmers to predict crop outcomes, promptly detect and manage diseases, and optimize irrigation and fertilization schedules with heightened precision and efficiency (Kendall et al., 2022). This study aims to explore the impact of data exchange and the integration of machine learning in precision farming within the Rwandan context. By examining these technological advancements and their practical applications, the study seeks to uncover opportunities to maximize agricultural productivity, promote sustainable farming practices, and address the unique challenges faced by Rwanda's agricultural sector (Randell & Mccloskey, 2014). Ultimately, this research aims to contribute to the advancement of agricultural innovation and economic development in Rwanda through the widespread adoption of precision farming technologies("Influence of Agricultural Project Management Practices on Agricultural Production: Case Study of Musanze District, Rwanda," 2024).

Despite advancements in precision farming, there remains a gap in effectively harnessing machine learning and data exchange to provide actionable insights for crop production. The challenge lies in integrating diverse environmental parameters into predictive models and ensuring seamless data flow among various sources to offer personalized recommendations for farmers(Akkem et al., 2023). Indeed, precision farming can also reduce pesticide use and optimize water management, leading to more environmentally sustainable agricultural practices. By utilizing advanced technologies and data analytics, precision farming allows for precise application of inputs like water, fertilizers, and pesticides based on real-time data and specific needs of crops. This targeted approach minimizes waste, reduces the environmental footprint, and promotes the health of the ecosystem(Parra-López et al., 2024).

For instance, precision farming techniques can identify pest infestations early and apply pesticides only where needed, rather than blanket spraying entire fields. Similarly, soil moisture sensors and weather data can guide irrigation practices, ensuring that crops receive the right amount of water at the right time, thereby conserving water resources and preventing issues like soil erosion and nutrient runoff. These practices contribute to the overall goal of sustainable agriculture by enhancing efficiency, reducing negative environmental impacts, and supporting long-term agricultural productivity(Javaid, n.d.) (Getahun et al., 2024).The study have the following objectives: To investigate the potential of machine learning techniques and data exchange in precision farming. To develop predictive models that can optimize resource allocation and crop management. To establish a robust data exchange framework that facilitates real-time data sharing and analysis. To provide actionable insights and personalized recommendations for farmers.

2. Literature Review

Global agricultural productivity must double by 2060 to meet growing demands, all without expanding arable land or causing significant environmental damage. Achieving this requires sustainable practices, such as reducing carbon emissions, preserving or enhancing soil quality, conserving water resources, and minimizing pesticide use. One effective approach is leveraging data-driven advancements like phenotyping, which focuses on breeding crops suited to specific farm conditions, such as soil type and rainfall, and adopting improved farming practices. However, a major challenge remains: the lack of manual data collection, which impedes the widespread adoption of data-driven agriculture on farms. Previous research highlights the importance of precision farming in improving crop yields and resource utilization (Karunathilake et al., 2023). Technologies like IoT, remote sensing, and GIS are used to monitor environmental parameters(Kundan et al., 2024).

Precision farming, also known as precision agriculture, refers to a set of practices that utilize advanced technologies and data-driven methods to optimize crop production and resource use. It involves the application of precise amounts of inputs (such as water, fertilizers, and pesticides) based on detailed information about field variability. The core principles include data collection through sensors and satellites, data analysis, and precise management actions tailored to the specific needs of different areas within a field(Soussi et al., 2024). Precision farming has become a pivotal approach in modern agriculture due to its ability to significantly enhance productivity and sustainability. By using technology to monitor and manage crops with high accuracy, farmers can achieve higher yields, reduce waste, and minimize environmental impact. Globally, precision farming contributes to more efficient use of resources, reduced input costs, and improved soil health, which collectively support sustainable agricultural practices and food security(R. K. Singh et al., 2021).

Data-driven agriculture(Soussi et al., 2024), precision agriculture(Mesías-Ruiz et al., 2023), smart farming, and machine learning(Elashmawy, 2023) are all related to the use of technology to optimize and improve agricultural practices(Mekonnen et al., 2020). Data-driven agriculture refers to the use of data and analytics to inform decision-making in farming, from planting to harvesting(Mesías-Ruiz et al., 2023). This approach involves collecting and analyzing data on soil health, weather patterns, and crop performance to optimize agricultural practices and improve yield. Precision agriculture is a farming technique that uses technology such as sensors(Tantalaki et al., 2019), GPS, and drones to collect data on soil and weather conditions(Vrchota et al., 2022), crop health, and nutrient levels(Sharma et al., 2021). This data is then used to make informed decisions about irrigation, fertilization, and other inputs to optimize crop yields and reduce waste(Dhanaraju et al., 2022).

Smart farming refers to the use of connected devices and data analytics to optimize various aspects of farming(Chergui & Kechadi, 2022), such as irrigation, fertilization, and crop monitoring(Said Mohamed et al., 2021). This approach involves using sensors, drones, and other technology to collect data, which is then analyzed to make decisions about farming practices(Dhanaraju et al., 2022). Machine learning(Kamath et al., 2021) is a subset of artificial intelligence that involves training algorithms to identify patterns in data(Cedric et al., 2022). In agriculture, machine learning is used to analyze large datasets on soil health, weather patterns, and crop performance to identify trends and make predictions about future crop yields(Anjana et al., 2021). Machine learning can also be used to optimize irrigation and fertilization practices by providing real-time recommendations based on changing environmental conditions(Durai & Shamili, 2022). An IoT system for agriculture(Chergui, 2022) is a network of connected sensors and devices that can collect and analyze data about various environmental factors such as soil moisture, temperature, humidity, and light levels(Xu et al., 2022). This data is then transmitted to a central system where it can be analyzed and used to make informed decisions about farming practices(Moisa et al., 2022). For example, IoT sensors can be placed in soil to collect data on moisture levels(Rehman et al., 2022), and this information can be used to determine when to water crops and how much water to use. Similarly, sensors can be placed on plants to monitor their growth and health(Ando, 2022), and this information can be used to adjust fertilizer and pesticide applications(Katiyar & Farhana, 2021).

IoT systems can also be used for precision agriculture, where data is collected and analyzed at a very granular level(Khattar & Verma, 2023), allowing farmers to make very specific decisions about crop management. This can lead to increased yields, reduced costs, and better environmental outcomes(OECD, 2001). Overall, IoT systems for agriculture offer a range of benefits, including increased efficiency, improved sustainability, and better outcomes for farmers and consumers alike. The challenge with implementing an IoT system in agriculture(Akhter & Sofi, 2022; Dong et al., 2013) is the lack of internet connectivity and power in remote areas of farms. Additionally, the cost of deploying and managing a large number of sensors can be prohibitive. However, the ultimate goal of implementing such a system is to enable data-driven farming by providing real-time data to all stakeholders involved in agriculture, such as farmers, suppliers, distributors, and processors(Eprs & Parliamentary, 2023). The second goal is to develop models and analytics to improve farming practices, crop, and animal management(Mesías-Ruiz et al., 2023; Said Mohamed et al., 2021; Vrchota et al., 2022). The third goal is to automate systems for irrigation, pesticide, and spraying, which would allow for precision farming. By achieving these goals, farmers can make informed decisions that would improve crop

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yields, reduce the use of resources such as water and fertilizers, and ultimately make agriculture more sustainable and profitable.

Machine learning can also be utilized to predict crop yields and optimize planting schedules(Vignesh et al., 2023). By analyzing historical data on weather patterns and crop growth, machine learning algorithms can provide farmers with insights into when to plant their crops, how much to plant, and how to optimize their use of resources(Alibabaei et al., 2021). Overall, machine learning offers immense potential in farming, enabling farmers to make data-driven decisions, reduce waste, and increase productivity(Bali & Singla, 2022). Sensors are used to collect data on various environmental factors such as soil moisture, weather conditions, and crop health. Agriculture is a cornerstone of Rwanda's economy, employing a significant portion of the population and contributing substantially to the country's GDP. The sector primarily focuses on staple crops such as coffee, tea, and maize, which are crucial for both domestic consumption and export. Despite its importance, traditional farming methods often face challenges related to productivity and sustainability(*Research on World Agricultural Economy Comparative Analysis of Machine Learning Models for Predicting Rice Yield : Insights from Agricultural Inputs and Practices in Rwanda*, 2024).

Several factors are driving the adoption of precision farming in Rwanda, including the need to improve crop yields, manage limited resources more effectively, and address the impacts of climate change. Technological advancements, increased access to digital tools, and a growing emphasis on agricultural innovation are encouraging the transition to precision farming practices(Hitimana et al., 2024). The Rwandan government has introduced various initiatives and policies to support agricultural innovation, including the National Agriculture Policy and the Strategic Plan for the Transformation of Agriculture. These policies aim to promote technology adoption, enhance research and development, and improve infrastructure to facilitate precision farming practices(Shang & Xie, 2024).

Effective data exchange is crucial in precision farming as it ensures that accurate and timely information flows between farmers, agronomists, researchers, and technology providers. This collaboration facilitates better decision-making, enhances the accuracy of predictions, and allows for more responsive and informed interventions(Gawande et al., 2023). Examples from other regions highlight the benefits of data exchange in precision farming. For instance, in the United States and Europe, integrated data platforms enable real-time monitoring and management of crops, leading to improved outcomes and efficiency. These case studies demonstrate how seamless data sharing can drive innovation and success in precision agriculture(Mizik, 2023).

Machine learning (ML) plays a transformative role in precision farming by analyzing large volumes of agricultural data to uncover patterns and trends that are not immediately apparent. ML algorithms can process data from various sources, such as sensors and satellites, to provide actionable insights and predictions (Ibidoja et al., 2023). ML applications in precision farming include predicting crop yields, detecting diseases early, and optimizing resource management. For example, ML models can forecast optimal planting and harvesting times, identify pest infestations, and recommend precise amounts of water and fertilizers, leading to enhanced productivity and reduced input costs [9]. Worldwide, ML has been successfully applied in agriculture to improve efficiency and

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outcomes. For instance, ML algorithms have been used for yield prediction in the United States and disease detection in India. In Rwanda, similar applications could help optimize farming practices, improve crop resilience, and support sustainable agricultural development(Ariza-Sentís et al., 2024).

Rwanda faces several challenges in adopting precision farming, including infrastructure limitations, access to technology, and varying levels of data literacy among farmers. These obstacles can hinder the widespread implementation of advanced agricultural technologies (Musanase et al., 2023). Despite these challenges, precision farming presents opportunities to address key issues. For example, improved infrastructure and training programs can enhance technology adoption, while targeted policies can support access to necessary tools and resources. Leveraging precision farming can ultimately lead to increased productivity and sustainability in Rwanda's agricultural sector(Mcfadden et al., n.d.)(Jaramillo-Hernández et al., 2024). A review of existing studies and projects provides insights into the current state of precision farming in Rwanda. These studies offer valuable data on the effectiveness of various technologies and practices, highlighting successes and areas for improvement(Miklyaev et al., 2021). Analysis of research findings reveals the impact of data exchange and machine learning on precision farming outcomes in Rwanda. Insights gained include improvements in crop yields, better resource management, and enhanced decision-making capabilities (Condran et al., 2022).

The potential for scaling up precision farming practices in Rwanda is significant, given the country's commitment to agricultural innovation and technological progress. Expanding the adoption of precision farming can drive further improvements in productivity and sustainability(Araújo et al., 2023). Recommendations include investing in infrastructure, supporting research and development, and providing training programs for farmers. Engaging stakeholders and fostering collaboration can also enhance the effectiveness of precision farming initiatives(Widtayakornbundit & Luangpituksa, 2023). Future research should focus on developing cost-effective solutions, addressing data privacy concerns, and exploring new technologies. Innovation in these areas will be crucial for advancing precision farming and achieving long-term sustainability in Rwanda's agricultural sector(Kabirigi et al., 2023).

Table.1: Literature review based on soil content

Type of parameter	**Reference**	**publication year**	**accuracy**
Moisture (Water Level)	(Tzerakis et al., 2023)(López et al., 2022)	2023	±0.03 m3/m3
Soil Temperature	(Tzerakis et al., 2023)(D. K. Singh et al., 2022)	2023	±1◦C
Electrical Conductivity of the Soil (EC)	(Tzerakis et al., 2023)(Mirzakhaninafchi et al., 2022)	2022	±5% dS/m
Fertilizer levels of nitrate	(Assa et al., 2023)	2023	
Phosphorus	(Soil & Agriculture, 2023)	2023	
Potassium (NPK)	(Pyingkodi et al., 2022)	2022	60-70%
pH level	(Cheema et al., 2022)	2022	

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3. Methodology and Materials

Data collected from ulk land, Gisozi sector, Gasabo District, Kigali City, Rwanda using different soil sensors. Dataset are real time collected using seven different soil sensors such as soil moisture, temperature, humidity, azote, potassium, calcium, and pH in 24 hours we detect our model by predicting 1961 different data, find more details on https://github.com/bosuluss/soil_content_csv_ulk.git.

Figure 1: Soil Moisture Sensor.

Table 2: Soil Dataset Sample

	soil_moisture	soil_temperature	EC	nitrogen	potassium	\
0	39.0	23.4	101.35	0.46	10.83	
1	39.0	23.3	101.35	0.46	10.83	
2	39.1	23.3	101.35	0.46	10.83	
3	39.0	23.3	101.35	0.46	10.83	
4	39.1	23.4	101.35	0.46	10.83	
...	...	...	...	...	...	
1956	80.0	30.0	12.00	10.00	9.00	
1957	20.0	30.0	12.00	10.00	9.00	
1958	80.0	30.0	12.00	10.00	9.00	
1959	20.0	30.0	12.00	10.00	9.00	
1960	20.0	30.0	12.00	10.00	9.00	

	phosphorous	pH	batteryLevel
	4.72	7.9	90
	4.72	7.9	90
	4.72	7.9	90
	4.72	7.9	90
	4.72	7.9	90
.	...	...	...
56	31.00	7.0	90
57	31.00	7.0	90
58	31.00	7.0	90
59	31.00	7.0	90
60	31.00	7.0	90

961 rows x 8 columns]

Table 2 presents the soil dataset collected from ULK Land using a soil-sensing device, which contains 1962 data. The soil sensor dataset records various soil conditions measured by a device, including soil moisture, temperature, electrical conductivity (EC), nitrogen, potassium, phosphorous, pH level, and battery level. An ID and device ID, along with timestamps for when the data was created and last updated, uniquely identify each entry. The dataset captures regular measurements, such as soil moisture at around 39%, temperature at 23.4°C, and a pH of 7.9, with the device's battery consistently at 90%. This data provides valuable insights into soil health and can be useful for agricultural and environmental analysis.

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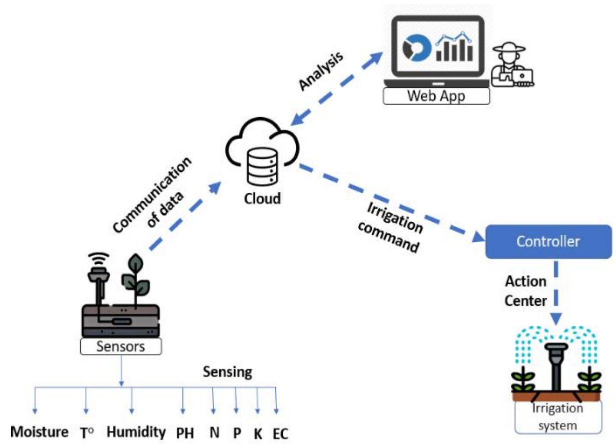

Figure 2: System architecture and recommendation daily practices for farmer beats

The figure 2 depicts an automated irrigation system that leverages sensor data and cloud-based analysis to optimize water usage in agriculture. Various sensors installed in the soil measure key parameters such as moisture, temperature, humidity, pH, NPK levels, and electrical conductivity. The collected data is communicated to a cloud system, where it is analyzed to make informed irrigation decisions. The results are displayed via a web application, allowing users to monitor soil conditions and system performance. Based on the analysis, the cloud sends irrigation commands to a controller, which operates the irrigation system, ensuring precise and efficient water delivery, conserving resources, and enhancing crop health.

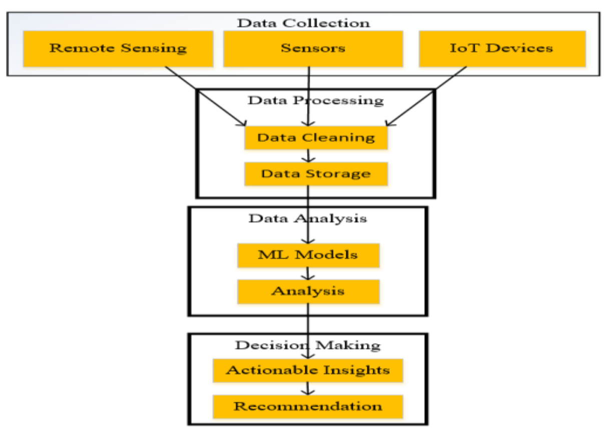

Figure 3: Conceptual Data Processing

Machine learning model development in precision farming involved evaluating algorithms like Linear Regression for crop yield prediction and Decision Trees for classifying soil health and disease risk. These models were trained on historical data and validated using cross-validation techniques, with performance measured through metrics such as accuracy, precision, recall, and F1-score. An advisory system was developed to provide personalized recommendations based on these predictive models. By integrating real-time sensor data and a robust data exchange framework, the system offers actionable insights to farmers via a user-friendly interface, supporting informed decision-making and improved agricultural practices. In this context, we applied a Random Forest Regression model, which plays a pivotal role in precision farming by analyzing data to deliver tailored recommendations, such as optimal irrigation schedules, fertilizer application rates, pest control strategies, and harvesting timelines. These insights enable targeted actions like variable-rate input applications and site-specific crop management, enhancing efficiency and reducing waste. Continuous monitoring establishes a feedback loop for real-time adjustments, allowing farming practices to adapt to changing environmental and market conditions. The framework emphasizes sustainability by optimizing resource use, lowering chemical inputs, and boosting long-term productivity while minimizing environmental impact. The final prediction aggregates the outcomes from individual trees. The regression analysis using the Random Forest Regressor, based on the existing dataset of soil content, confirmed the model's efficacy in precision farming. Collaboration among stakeholders, including farmers, agronomists, researchers, and technology providers, ensures efficient data exchange and decision-making. Precision farming ultimately leads to higher yields, improved resource efficiency, cost savings, and sustainable practices that enhance food security and environmental conservation. Random Forest, an ensemble learning method, combines multiple decision trees to make predictions by constructing trees from different subsets of the training data and randomly selected features.

4. Results and Discussions

Once collected, the device sends the data to the cloud, where it is organized, analyzed, and displayed. The processed data is then made accessible via a web application, allowing users to remotely view and interact with the information. An embedded algorithm within the web application automatically triggers the irrigation system based on the analysis of fertilizer and water levels in the soil. This automation ensures the irrigation system operates at optimal times, maximizing the efficiency of water and fertilizer usage for improved plant growth and resource management. The architecture of a smart irrigation and fertilizer management system involves multiple components working together to optimize resource usage. Sensors are deployed in the field to monitor key soil parameters such as moisture, temperature, electrical conductivity (EC), and nutrient levels. A data acquisition module collects real-time data from the sensors, transmitting it to a central system or cloud platform via communication protocols like Wi-Fi, cellular networks, or LoRaWAN. Once in the cloud, the data is stored, managed, and processed using scalable storage and computational resources for effective data handling. The cloud platform processes the data using algorithms and machine learning techniques to analyse soil conditions, determine irrigation requirements, and assess nutrient needs. Based on this analysis, the system makes intelligent decisions about irrigation scheduling and fertilizer application by following predefined rules or predictive models that consider plant needs, weather conditions, and soil characteristics. These decisions are sent to a control system that manages irrigation infrastructure, controlling elements like valves, pumps, and sprinklers to deliver water and nutrients precisely. A user interface, accessible via a web or mobile app, allows users to monitor real-time data, adjust settings, and receive notifications, while a feedback loop continuously refines the system's performance, enhancing decision-making and optimizing resource use.

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Figure 4: Deployment of a soil monitoring system, utilizing sensors and IoT-enabled devices, to measure soil conditions and composition accurately.

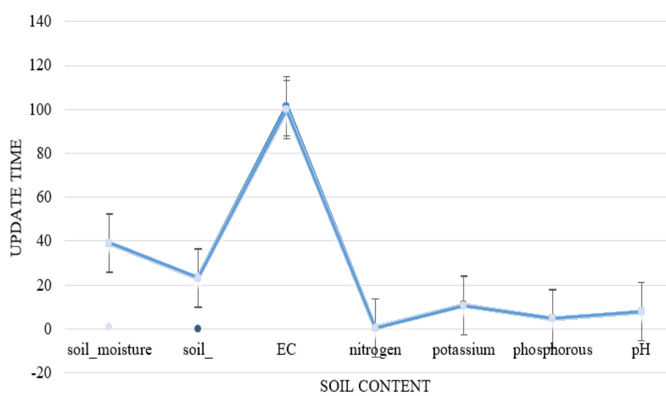

Figure 5: Soil content collected through the system.

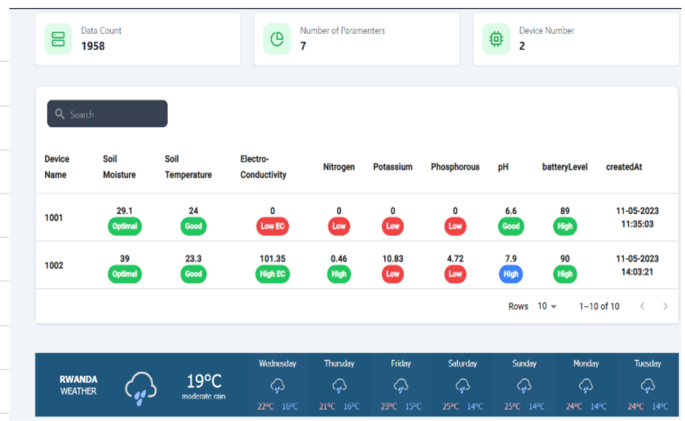

Figure 6: A web platform to monitor soil content with two devices, one in the field and the other in the workshop

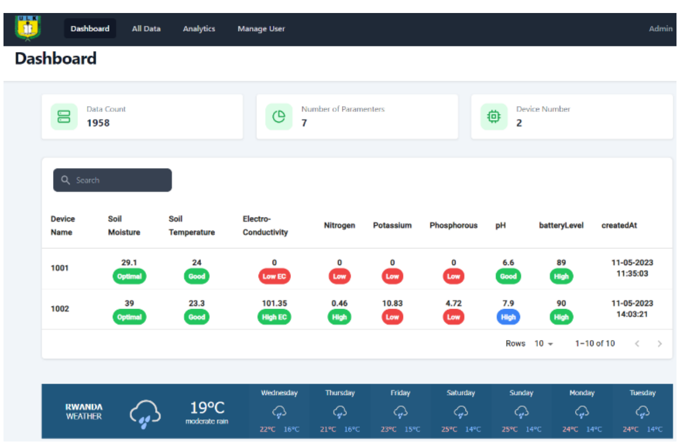

Figure 7: Dashboard for seven parameters of soil status through different time.

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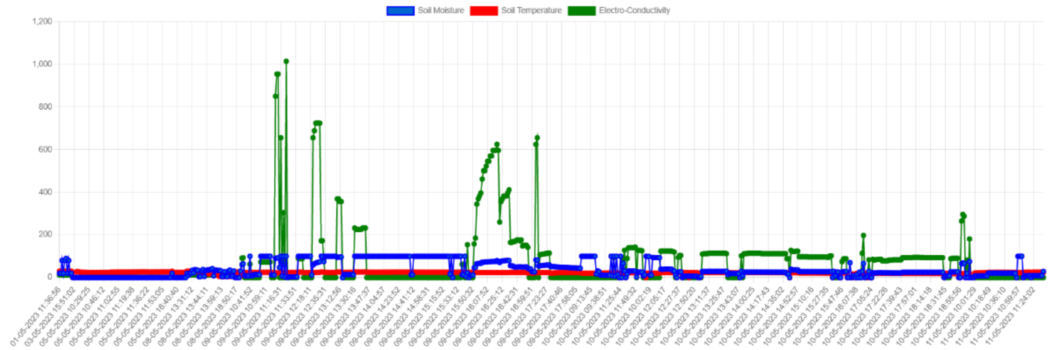

Figure 8: Soil moisture monitoring for seven parameters of soil status through different time.

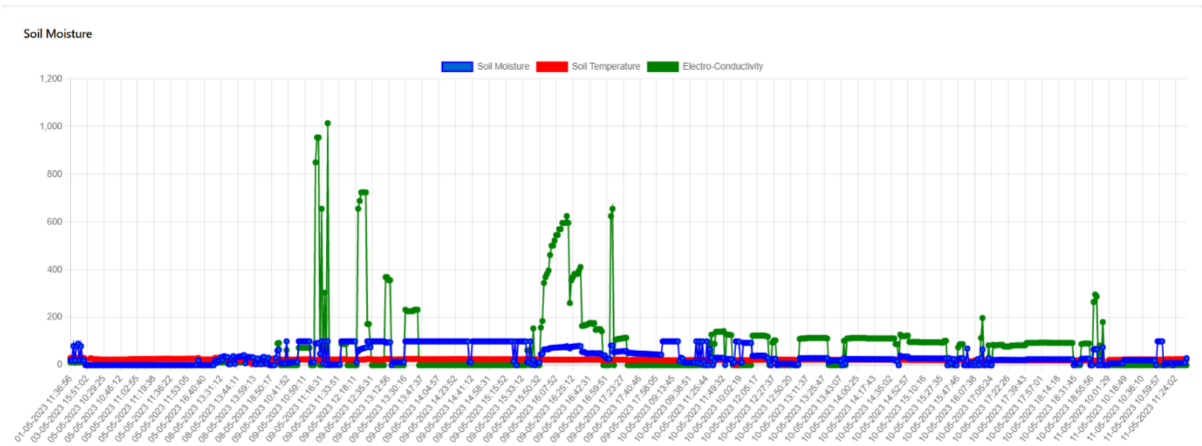

Figure 9: Soil moisture, soil temperature, and electro-Conductivity monitoring of soil status through different time.

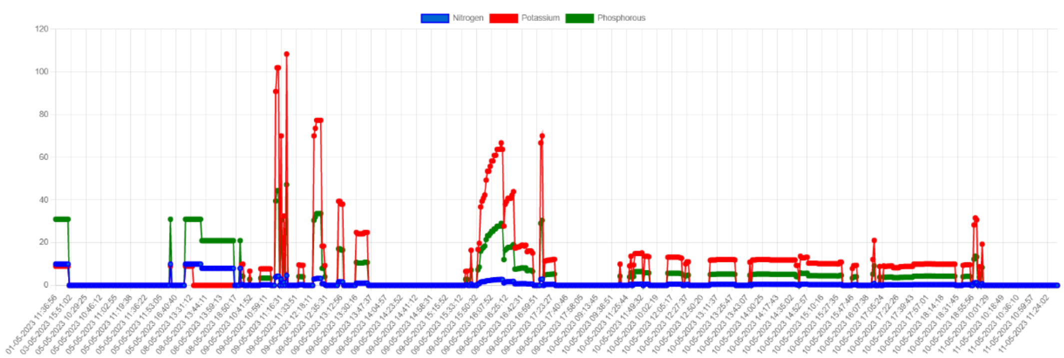

Figure 10: Nitrogen, potassium, and phosphorus monitoring for seven parameters of soil status

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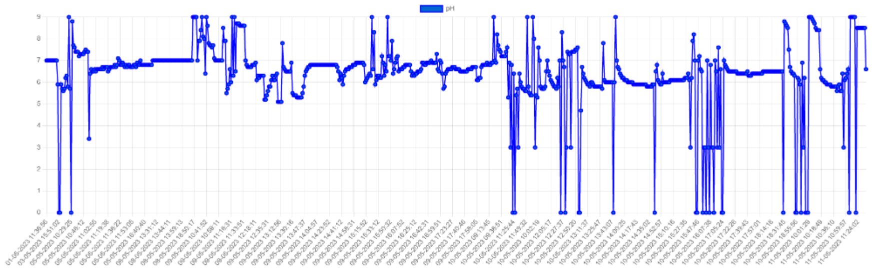

Figure 11: pH monitoring of soil status through different time.

A robust data exchange framework was established to facilitate real-time data sharing among various stakeholders. The framework ensured seamless integration of data from different soil sensors sources, standardized data formats, and secure data transmission protocols. The fable 3 explain statistical interpretation of data preprocessing by normalization and missing values.

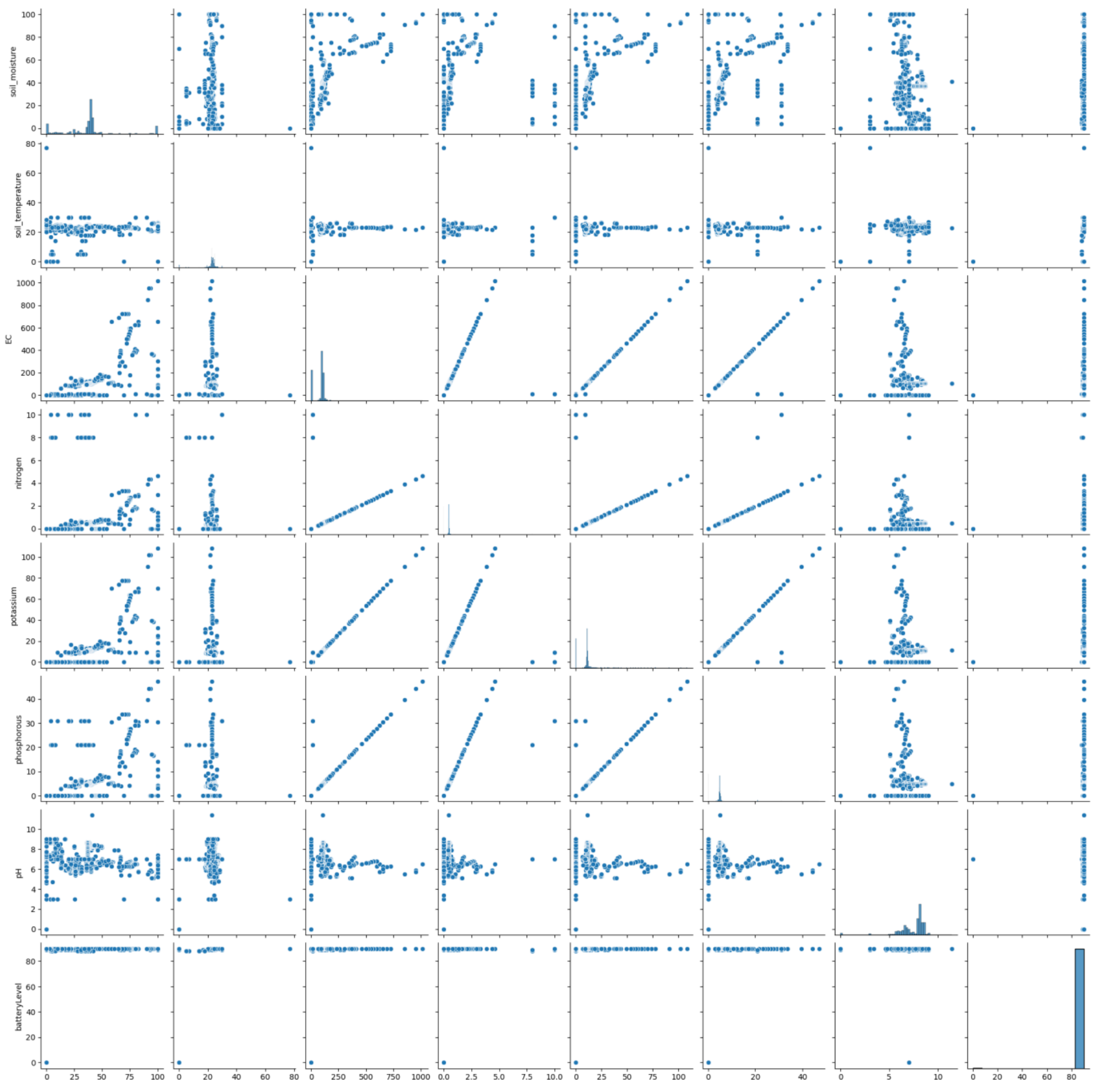

Figure 12: data visualization for all seven parameters

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The implementation of conceptual framework comprehensive implementation of a Random Forest Regressor model to predict soil pH based on various soil content attributes. It begins by importing essential libraries such as pandas for data manipulation, numpy for numerical operations, and several visualization tools (matplotlib and seaborn) for data exploration. The dataset is loaded from an scv file, and the numeric columns representing soil attributes (soil moisture, temperature, EC, nitrogen, potassium, phosphorous, battery level, and pH) are extracted into feature (X) and response (y) variables. The soil content attributes are then printed in a table 1, followed by a pyplot to visualize relationships between variables. The data is scaled and normalized using StandardScaler, and a bar plot is generated to show the average weight of each soil attribute.
Next, the step splits the dataset into training and testing sets (80% for training and 20% for testing). It also handles missing values by reading and cleaning the training and testing files, converting non-numeric columns to datetime, and ensuring all relevant columns are numeric. After cleaning the data, the model is trained using the Random Forest Regressor on the training data, and its performance is evaluated using the R^2 score. Finally, the model's predictions are visualized by comparing actual versus predicted values in a scatter plot. This allows for an assessment of how well the model can predict pH values based on the provided soil attributes with 99.9 % accuracy.

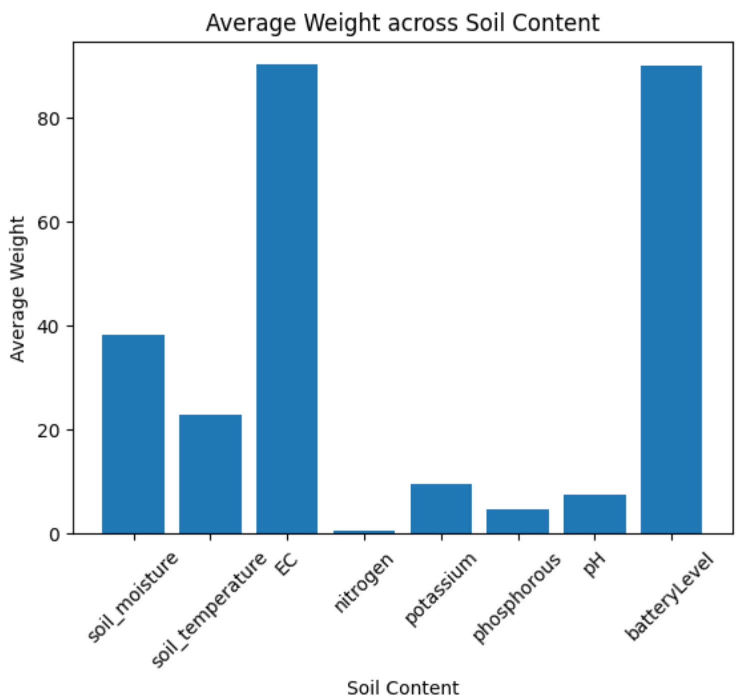

Figure 13: Visualization of a dataset Average Weight across soil content

The Figure13 illustrates the relative importance of various soil content factors in a farming context. The x-axis lists factors such as soil moisture, soil temperature, electrical conductivity (EC), nitrogen, potassium, phosphorus, pH, and battery level, while the y-axis represents their average weight. Notably, EC and battery level have the highest weights, indicating their significant influence. Soil moisture and temperature also show substantial importance. In contrast, nitrogen, potassium, phosphorus, and pH have lower weights, suggesting they are less critical in this specific analysis. The inclusion of battery level likely

https://dx.doi.org/10.4314/ulksj.v46i1.1

pertains to sensor performance monitoring. This chart highlights the prioritized factors in the farming system under study.

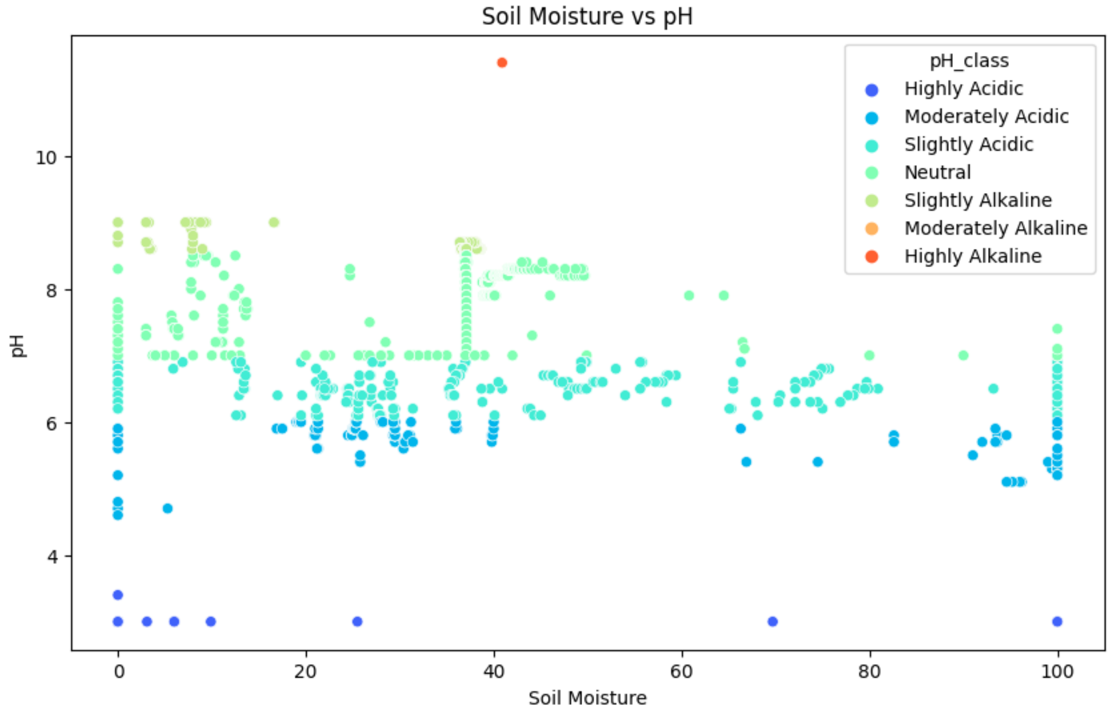

Figure 14: This image represents a simple Decision Tree Regressor for predicting crop yield

The R^2 score of 0.999 suggests that approximately 99.9% of the variance in pH values can be explained by the predictor variables used in the Random Forest Regressor model, indicating a strong relationship between the features (such as soil moisture, temperature, EC, nitrogen, potassium, phosphorous, and battery level) and the target variable (pH). This high R^2 score demonstrates that the model can effectively predict pH values, making it valuable for soil analysis and agricultural applications. It can help predict soil pH based on various factors, providing useful insights for farmers, researchers, or environmentalists to optimize crop growth, assess soil health, and make informed decisions about fertilization, irrigation, and pH adjustments. However, the model's results should be interpreted with domain knowledge, considering other potential influencing factors not included in the model, and further validation may be needed to ensure its accuracy and generalizability.

The analysis revealed significant correlations between environmental parameters and crop performance. For example, optimal soil moisture and temperature ranges were identified for different crop stages, guiding irrigation and fertilization practices. The red lines represent linear fits from the plots, and the regression equations can mathematically describe these linear fits. The slope of each line tells you how sensitive yield is to changes in each variable (N, P, K, temperature, humidity, pH, soil moisture). If the slope is close to zero, there is little to no relationship between the variable and yield. If the slope is large (positive or negative), it indicates a stronger relationship.

https://dx.doi.org/10.4314/ulksj.v46i1.1

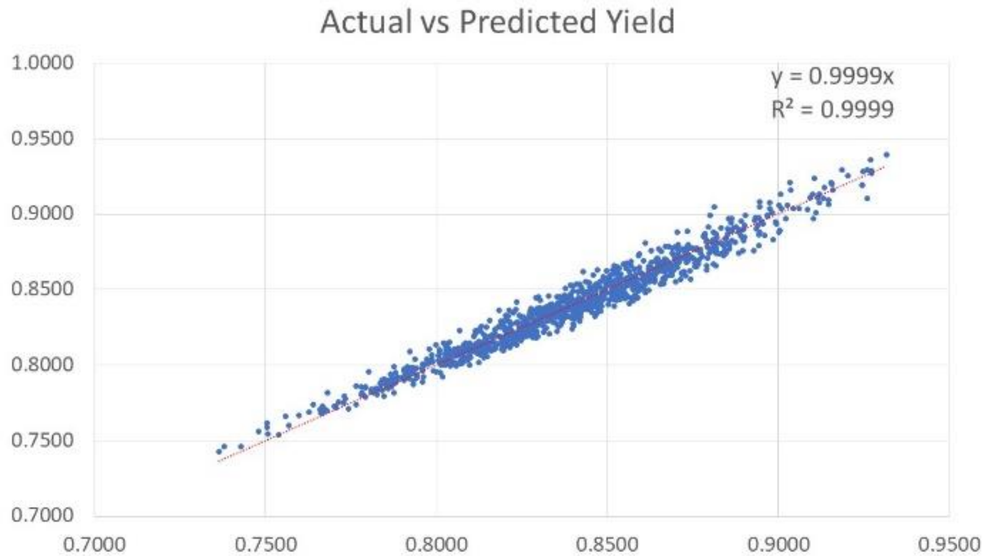

Figure 15: Actual Vs Predicted Yield Y=0.99, R^2=0.99

The machine learning models demonstrated high accuracy in predicting crop yields Figure (15) and identifying increase production. The multiple linear and lasso regression model, in particular, showed superior performance in handling large and complex datasets and the effectiveness of the predictive models in estimating the yield level based on various environmental and soil factors

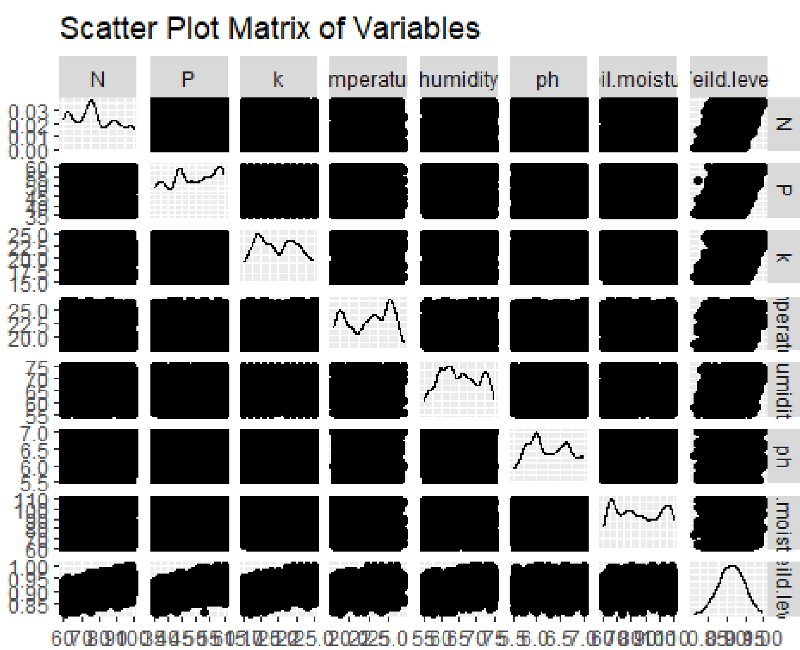

Figure 16: Scatter Plot Matrix of Variables

The MSE and RMSE values for both regression models are very low, indicating a good fit to the data. The slight difference between the MSE of the two methods indicates that Lasso regression might be marginally better due to its regularization properties, reducing over fitting.

$$y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n + \varepsilon \qquad Eq1$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2 \qquad Eq2$$

The data exchange framework demonstrated its effectiveness in enabling real-time data sharing and integration, which facilitated timely updates and accurate predictions, thereby enhancing the precision farming process. Additionally, farmers who utilized the advisory system reported increased yields and improved resource efficiency. The system's real-time recommendations allowed for timely interventions, reducing the risk of crop failure and optimizing the use of resources.

5. Conclusion

This study emphasizes the transformative potential of the Random Forest Regressor model, which achieved 99.9% accuracy in predicting soil pH and facilitating data exchange in agriculture. It highlights how these technologies can improve crop yields, optimize farming schedules, and foster sustainable practices. The developed advisory system exemplifies the practical use of data-driven decision-making, demonstrating its ability to tackle modern farming challenges. Continued advancements in these fields offer the promise of a more efficient and sustainable agricultural future.

Conflict of Interest

This work has no Conflict of interest

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