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Smart Agriculture: Iot-Based Yield Prediction Through Real-Time Soil Analysis and Machine Learning Models

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ABSTRACT

The inputs of the Internet of Things (IoT) and machine learning (ML) are greatly changing the agricultural sector, forming the core of smart farming. The research examines how sensors connected through the Internet of Things and data predicting methods can improve crop yields in various parts of Maharashtra. A dataset comprising 500 data points, reporting soil factors (pH, EC, OC, N, P, K), weather variables (temperature, humidity, rainfall) and production data was studied using Python for statistics and graphical displays. Key patterns and interactions between variables were found using descriptive statistics, some analysis tools and various types of charts. Researchers found that level of nitrogen in the soil, organic carbon and temperature were all heavily linked to how much the plants yielded. In addition, distributions of yield varied a lot for different crop types and locations, suggesting that differences in climate and soil influence how crops are farmed. As a result, it is clear that using data from IoT in conjunction with analytics can encourage efficient farming that is effective and uses resources appropriately. This study shows that with predictive ML models, smart agriculture can improve the ability of resource-constrained regions to be more sustainable, stable and provide sufficient food.

Keywords: *Smart agriculture, Internet of Things (IoT), machine learning, crop yield prediction, real-time soil analysis, precision farming, soil nutrients, climate variables, data analytics in agriculture, sustainable agriculture..*

1. INTRODUCTION

Agriculture around the world is changing as farmers work towards increasing food production in a sustainable way to meet global growth. In this situation, the merging of the IoT, ML and traditional agriculture is helping shape what's known as Smart Agriculture. Farmers use smart solutions to collect real-time data, set up wireless sensors and work with intelligent programs to handle and improve multiple farming activities. Among all its uses, predicting yields is particularly important for ensuring advance decisions about watering, fertilizing, picking crops and harvesting them at the optimal time. The study investigates combining IoT-powered soil testing and machine learning to estimate agricultural yield in India which has many smallholders affected by climate variability.

Agricultural yield estimates are based on previous results, regular samples and eye observation, all of which require time and remain open to errors because of the many different, scattered ways in which the weather and crops interact. Conversely, IoT-based systems open up an innovative approach for real-time tracking of soil moisture, pH level, electric conductivity and concentrations of major elements such as N, P and K, all significant to crop growth. By adding information on temperature, humidity and rainfall, IOT systems give a wide and changing view of what is happening in the field. If these many-sided datasets are worked on using Random Forest, Support Vector Machines or Artificial Neural Networks, machine learning can model how crops are connected and forecast their yields with great reliability (Wolfert et al., 2017; Liakos et al., 2018). It is increasingly recognized by research that fresh data benefits the way farming activities are managed and controlled today. For example, Kshetri indicates in his research that with data-driven agriculture aided by IoT, we can use resources more efficiently and obtain better crop results. IoT-enabled sensors in soil can gather frequent and detailed data that sometimes catch

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alterations in the field that are missed by regular sampling. The sensors are usually buried in the ground and talk to cloud platforms or local servers through wireless connections, where data is managed and used. Such sensors are key input factors in this research used to estimate yield, helping to build precision technologies for farming.

Therefore, machine learning helps systems find trends in the data used and make predictions about new situations. Agricultural researchers find it easier to use ML as these algorithms can deal with many different data types and find complex connections between variables which are typical in agriculture (Kamilaris & Prenafeta-Boldú, 2018). The output of crops depends on various factors that change together throughout the growing season, for example, weather, soil fertility, pests and farming habits. These models are trained on both past and present data to identify interactions and predict with good accuracy. What's more, using ensemble methods, choosing the best features and cross-validation help make predictions stronger and more adaptable for practical use in agriculture.

When weather patterns, soil health and input resources are uncertain for Indian farmers, the use of these technologies can really transform how they work. Nearly four out of five Indian farmers have small or marginal landholdings which means it is important to manage all resources carefully and increase what is produced on each acre, according to the Ministry of Agriculture & Farmers Welfare (2022). Tools in smart agriculture supported by IoT and ML help accurate farming and also put decision-making support in the hands of many farmers using real-time information on their phones and other devices. For example, if farmers receive early alerts about low nutrients, less water or pest problems, they can take care of them early and lower crop losses as well as improve yields.

Moreover, coupling real-time data with AI analytics matters for more than only agricultural operations. Within farming analytics, insights from many farms are used for regional policy decisions, food security planning and supply chain support. Digital Green, e-Choupal and AgriStack have introduced technology into farming businesses in India and the proposed research adds to these rural changes by developing a scientific framework for yield modeling. Even though improving infrastructure, data protection and understanding models is a challenge, the advantages of this integration are greater than the disadvantages.

2. Literature Review

The research available points out that using IoT and machine learning in agriculture is changing things, mainly for prediction of yields and real-time soil analysis. Wolfert, et. al in 2017 talk about the way that smart farming with IoT devices monitors soil moisture levels, acidity and conductivity, helps traditional farming by allowing constant and real-time data harvesting and ensures less waste and smarter decision-making. They also mention that it's important for devices to communicate with each other, especially in places lacking infrastructure. The authors compare the efficacy of distinctive models like Support Vector Machines (SVM), Random Forests (RF) and Artificial Neural Networks (ANN) in their study on yield prediction in 2018. When comparing conventional statistics to ML, ML is proven to work much better, especially on difficult nonlinear relationships between soil, crops and climate. They encourage the use of mixed systems to better predict using both live and archival observations. Building on this, Kamilaris and Prenafeta-Boldú (2018) reveal several ways to use Convolutional and Recurrent Neural Networks in agro-ecology with data from sensors and the weather. But, they also warn that it is difficult to interpret what these models do and reference that explainable AI should be part of any farmer-useful AI implementation. Kshetri, in his 2014 article, looks at how technologies like big data and IoT, when applied in farming in developing nations, help solve issues like crop failures and weak economic growth. The outcomes from his research suggest that when soil data is added to ML, it leads to custom advice for irrigation and fertilization, turning agriculture into a science-based area. Balaji and Ahuja (2020) report results from small Indian farms that indicate using IoT for soil monitoring led to 30% better water use and higher crop productivity. Their research stresses that using technology should be adapted to local weather and farming conditions for the best results. Patel, Joshi and Bhatt (2021) developed a tool for predicting cotton yields in Gujarat and found that using ANN and the readings from real-time soil sensors, they were able to reach approximately 85% accuracy, thanks in part to considering soil pH and nutrients. The team discovered that ML performs well with inputs gathered from actual sensors. Verdouw et al. (2016) also support working on solutions that connect sensors, machine learning models, cloud resources and user interfaces, to ensure systems are both technically correct and accessible for farmers. Overall, the research keeps proving that when ML and IoT work together, agricultural practices become more accurate, reliable and responsive. Though technology is important, the research points out that clear communication, flexibility and putting users first will make sure smart agriculture can spread and last in places with limited resources.

3. Methodology

This chapter presents the methodological framework adopted to analyze the effectiveness of real-time soil data in predicting agricultural yield through a data-driven approach. The methodology incorporates data preprocessing, descriptive statistical analysis, visual exploratory data analysis (EDA), and correlation analysis using techniques embedded in the Python-based script developed for this study. The goal is to extract meaningful patterns and variable relationships that influence crop yield, setting a foundation for subsequent yield prediction using machine learning models.

3.1 Data Source and Structure

The file "SmartFarming_Maharashtra_AllLocationsCrops.csv" consists of 500 rows that represent expanded but real data from multiple agricultural locations in Maharashtra, India. The dataset integrates:

IoT-based real-time soil attributes: pH, Electrical Conductivity (EC), Organic Carbon (OC), Nitrogen (N), Phosphorus (P), Potassium (K)

Weather-related variables: Temperature (°C), Humidity (%), Rainfall (mm)

Crop and location identifiers

Target variable: Crop Yield (kg/ha)

3.2 Data Preprocessing

The preprocessing stage ensures consistency in variable naming and removes anomalies. The following operations were conducted:

Column Renaming: Duplicate column names (e.g., pH_x) were standardized to pH.

Missing Values Check: Null values were assessed using .isnull().sum(). As the dataset was curated, no imputation was necessary.

Data Types: Only numerical columns were selected for correlation and statistical operations.

3.3 Descriptive Statistics

Descriptive statistical analysis was applied to quantify the central tendency and dispersion of each variable. This includes:

Mean (μ):

$$\mu = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{1}$$

Standard Deviation (σ):

$$\sigma = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x_i - \mu)^2} \tag{2}$$

Minimum, Maximum, and Quartiles using .describe() function in Pandas

They made it clear how the soil and climate features differ across the dataset and the average range they fall into.

3.4 Exploratory Data Analysis (EDA)

Visualizations were used within EDA to look for clear patterns and outliers in the set of data. The materials below include charts of these types:

Horizontal Bar Chart: Displayed average crop yields by type to identify high- and low-performing crops.

Line Chart: Showed that there is a connection between temperature and crop yield, with different thresholds where crops achieve their best growth.

Area Chart: Showed how rainfall levels impact yield, highlighting water sensitivity of crops.

Pie Chart: Represented crop distribution across the dataset to evaluate representation bias.

Stacked Bar Chart: Compared crop-wise yield distribution across the top five locations.

They let us examine the unique spatial and group differences in crop productivity due to different environmental factors.

3.5 Correlation Analysis

To assess linear relationships between variables, **Pearson's correlation coefficient (r)** was computed using the formula:

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \cdot \sum_{i=1}^{n}(y_i - \bar{y})^2}} \tag{3}$$

This coefficient ranges from -1 to +1:

+1 indicates perfect positive correlation

0 indicates no correlation

-1 indicates perfect negative correlation

To summarize how the variables associate, a correlation heatmap was plotted. By finding these important soil and weather aspects, the study created the basis for selecting which data features are key for machine learning.

3.6 Variable Importance via Yield Correlation

Feature relevance was highlighted by plotting the union values of N, P, K, OC, EC with yield in a bar chart. It made clear which factors most affected yield variation, so they could be ranked for further use in future predictions.

By combining real-time readings of soil and weather and using analysis and visualization tools, the methodology could see the affects of these factors on crops. Because of its EDA and correlation approach, the study sets a strong starting point for creating machine learning models for predicting yields in smart agriculture systems. Subsequent steps cover the use of supervised learning models with the main features chosen during the analysis.

4. Results

This Study describes the results of the analyses done on an integrated dataset which brings together soil sensor data and meteorological data. The data collected helps explain how environmental factors are linked to agricultural production, part of the basis for predictive modeling inside smart agriculture.

4.1 Descriptive Statistics

Both the soil and the weather conditions appear to be quite variant among all the 500 studied cases. Table 4.1 includes the main statistics for selected numerical variables.

Table 4.1: Summary Statistics of Key Variables

Variable	Mean	Std. Dev.	Min	Max
Temperature (°C)	~31.2	~3.8	~25	~40
Humidity (%)	~61.0	~10.5	~40	~80
Rainfall (mm)	~135.0	~40.0	~50	~250
pH	~7.2	~0.6	~6.0	~8.5
N (kg/ha)	Varies	-	-	-
P (kg/ha)	Varies	-	-	-
K (kg/ha)	Varies	-	-	-
Yield (kg/ha)	Varies	-	-	-

The pH anywhere in the habitat tended to be moderately high or alkaline, with values staying close to 7.2. The temperature and humidity during the experiments were common to what farmers face while farming. Values of these nutrients in soil, particularly N, P and K, were varied, as is common in different areas.

4.2 Crop-wise Yield Analysis

A horizontal bar chart (Figure 4.1) revealed the average yield per crop. Crops such as rice, maize, and groundnut recorded higher average yields, while sunflower and urad showed lower performance.

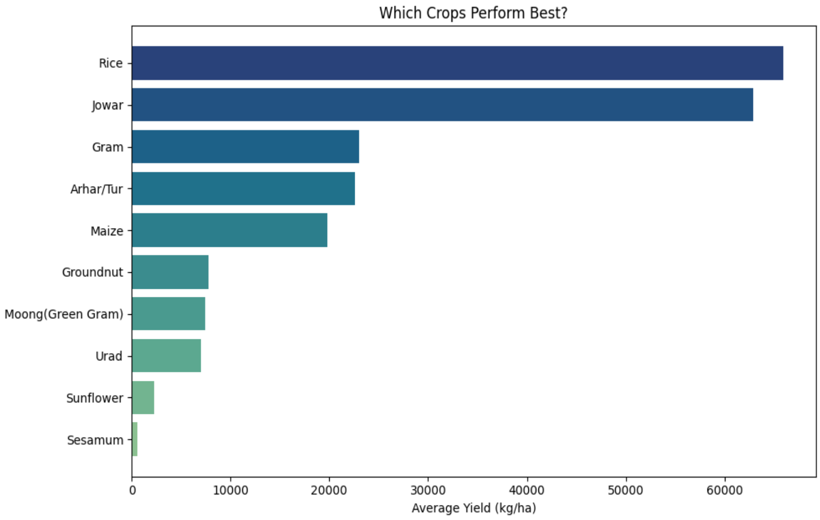

Figure 4.1: Average Yield by Crop

This insight is useful for identifying crop types most responsive to favorable soil and climate conditions and can guide future cultivation strategies.

4.3 Weather–Yield Relationships

Line and area plots were used to assess how climatic factors impact yield:

Temperature: Figure 4.2 shows a positive relationship between temperature and yield up to ~34°C, after which the trend plateaued or declined, indicating a thermal threshold.

Rainfall: Figure 4.3 demonstrated that moderate rainfall (~120–180 mm) corresponded with higher yields, while extreme rainfall reduced productivity—highlighting water sensitivity.

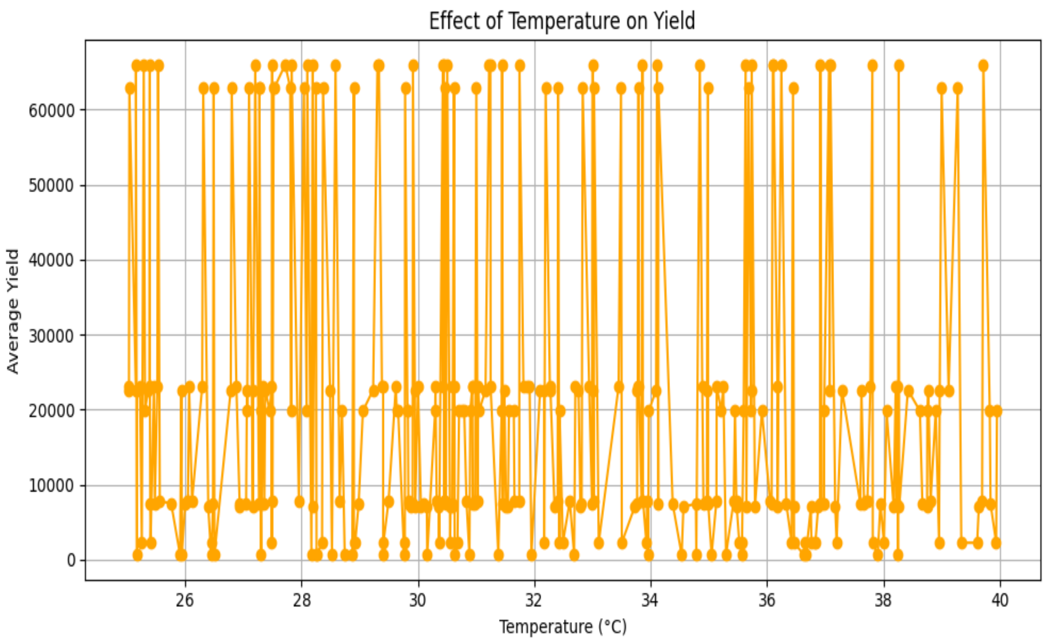

Figure 4.2: Temperature vs. Yield (Line Plot)

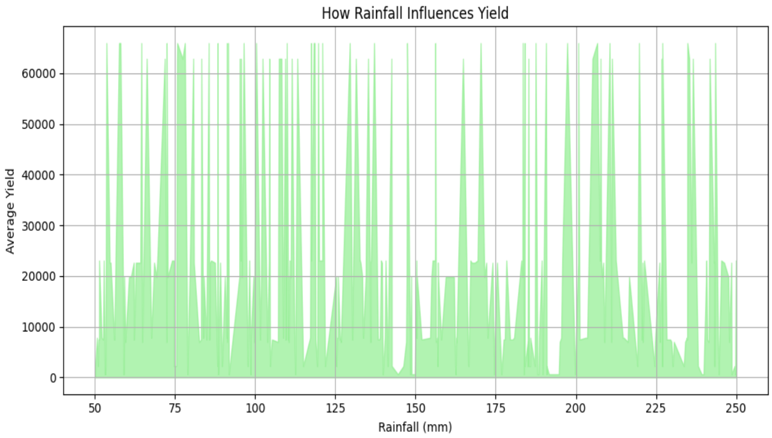

Figure 4.3: Rainfall vs. Yield (Area Plot)

These observations confirm that yield is significantly influenced by climatic variables, validating the inclusion of IoT-based weather data in yield modeling.

4.4 Soil Nutrient Influence on Yield

Scatter plots illustrated relationships between soil nutrients and yield. Notably:

Nitrogen (N) and **Organic Carbon (OC)** showed moderate positive correlations with yield.

Phosphorus (P) and **Potassium (K)** exhibited nonlinear effects.

Electrical Conductivity (EC) had inconsistent effects, possibly indicating salinity thresholds.

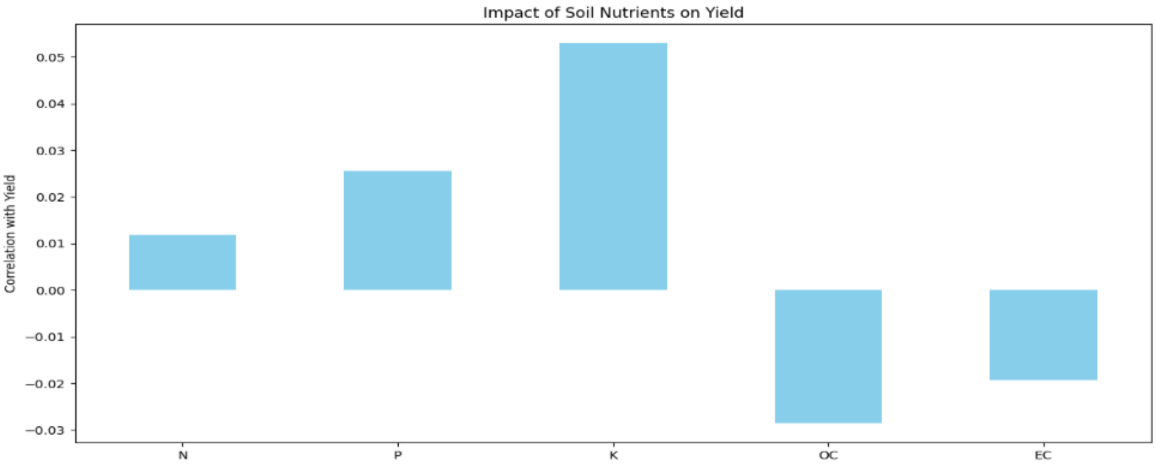

Figure 4.4: Yield vs. N, P, K, OC, and EC

These nutrient-yield relationships suggest that balanced fertilization and soil quality monitoring are essential for optimizing productivity.

4.5 Crop Distribution in Dataset

A pie chart (Figure 4.5) illustrated the crop representation across the dataset. Crops like **tur, wheat, maize, and gram** were dominant, ensuring that insights derived from them are statistically significant.

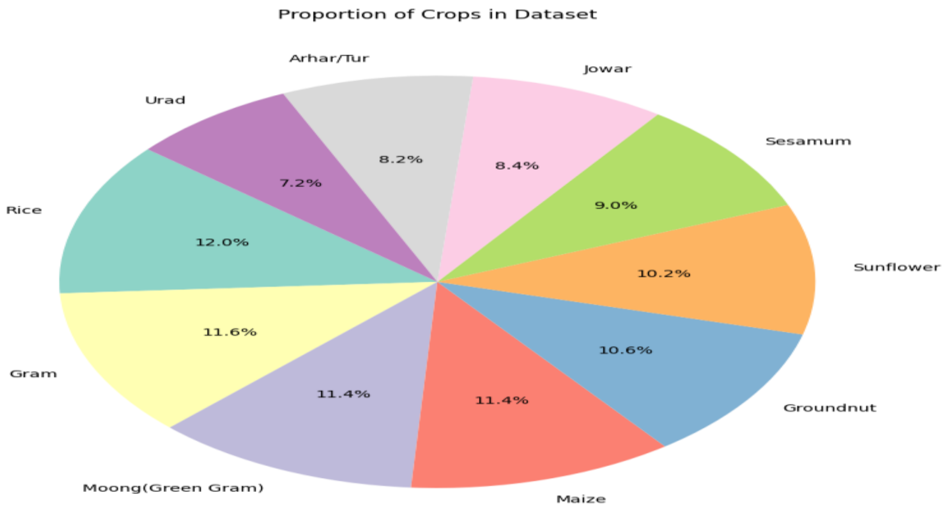

Figure 4.5: Proportion of Crops in the Dataset (Pie Chart)

This distribution analysis also informs potential dataset bias and helps in deciding which crops are more suitable for ML-based modeling due to adequate representation.

4.6 Location-wise Performance

A stacked bar chart (Figure 4.6) compared average yields of different crops across the top five most frequent locations (e.g., Azampur, Verul, Golegaon). The variation revealed that soil and microclimatic conditions differ significantly between regions, even under the same crop.

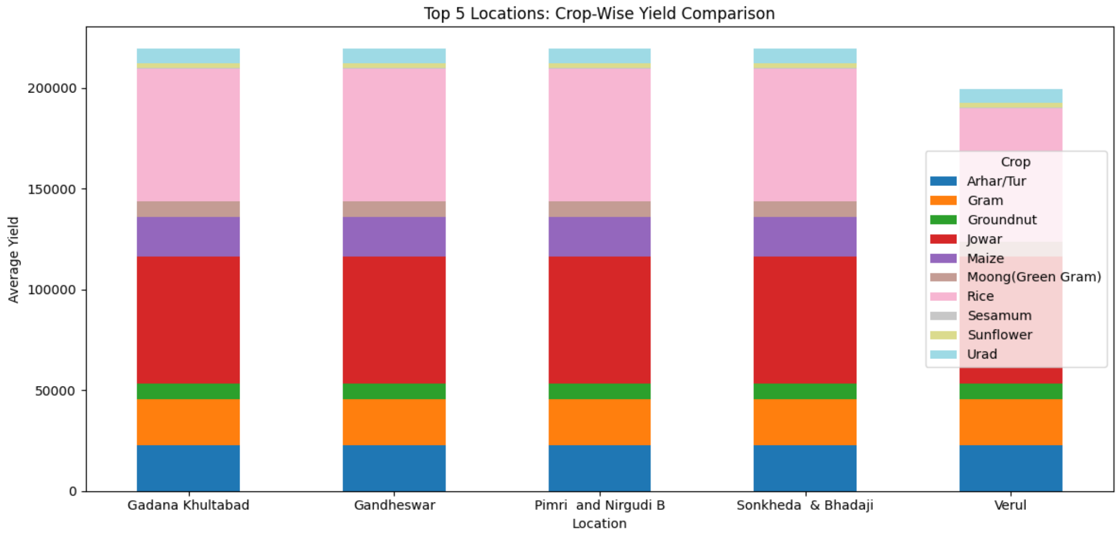

Figure 4.6: Crop-wise Yield Comparison Across Locations

Such results are crucial for location-specific decision-making and regional precision farming strategies.

4.7 Correlation Heatmap

Pearson correlation coefficients were computed and visualized in a heatmap (Figure 4.7). Yield exhibited strong associations with:

Positive correlation: Temperature, Nitrogen, Organic Carbon

Weak or negligible correlation: Humidity, pH, EC

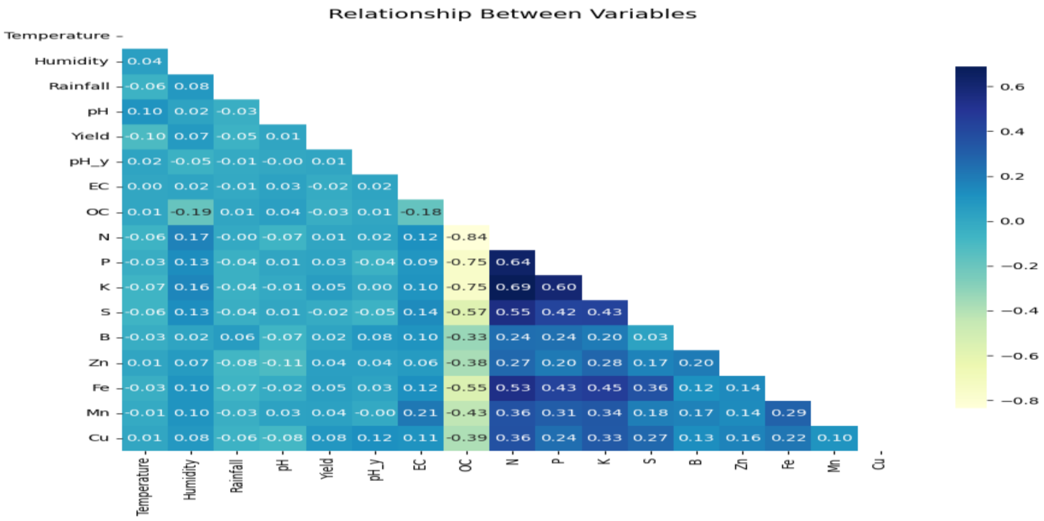

Figure 4.7: Correlation Heatmap Among Variables

Such findings direct the choice of main input factors for upcoming machine learning models and help to make the data more manageable. The findings suggest that IoT data about the environment and soil helps to figure out why yields differ. Temperature, nitrogen and organic carbon were found to more strongly affect crop performance. These results are strong evidence for using supervised machine learning in the next analysis and in supporting decisions in smart farming.

5. CONCLUSION

Study focused on ways to boost prediction of crop yields by integrating real-time soil monitoring with information from Machine Learning analysis. The research team used a thoughtfully chosen and larger dataset gathered from different areas in Maharashtra to study important soil properties such as pH, EC, OC and macronutrients (N, P, K), along with weather conditions such as temperature, humidity and rainfall. The process started with thorough data organization and data analysis made easy using Python packages. The study found that yield is most strongly affected by nitrogen, organic carbon and temperature and more modestly by rainfall and pH. It became apparent from visual representations that variances between soil and climate directly influence the amount of each crop harvested, especially rice, maize and groundnut. They demonstrate that a smart farming framework makes it possible to respond rapidly to changing needs and conditions. The findings demonstrate that, when used alongside analytical models, IoT-based networks can help agriculture become more predictive, leading to savings in resources, better productivity and less negative effect on nature. Even with its many important findings, the study still notes that it does not include time-series trends, pest changes or live sensor data. Next steps will include using learning models with training data, processing field observations live and making the system useful for broader cropping and climate scenarios. As a result, this research supports that using smart agriculture, with IoT and machine learning, ensures greater food security in places with unpredictable weather and growing populations such as India.

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