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Original Article

Smart Precision Agriculture using IoT Sensing and Machine Learning Analytics for Farming in Mysuru District

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Abstract - *Precision farming has been found to be a viable solution to the problem of productivity, sustainability, and resource efficiency of the rural agricultural sector in India. In this paper, I introduce a combined Internet of Things (IoT) and Machine Learning (ML)-based precision farming system to be used in real-time monitoring of soil health and predicting crop yields, including a comprehensive case study performed in the Mysuru district of Karnataka, India. One complete set of 557 farm records of 7 taluks in Mysuru, and another 50 comparison records in adjacent districts, were taken, including basic parameters like temperature, humidity, soil pH, soil moisture, light intensity, nutrient level (N, P, K), and yield/acre. A multi-sensor hardware platform (along with a Soil Information System (SIS)) was created together with cloud storage and a mobile-based decision-support application that will allow acquiring data continuously and provide feedback to the farmer. Three machine learning models, Support Vector Machine (SVM), Random Forest (RF), and Decision Tree (DT), were then trained on the preprocessed data consisting of normalized, imputed, and outlier-treated data to predict yields and compare them. As illustrated in experimental results, the Random Forest model performs better in terms of accuracy of 95.7 percent and a lesser prediction error on the Mysuru dataset compared to the SVM and DT models and models trained on neighboring district data. The results also show that the Mysuru soils have more coherent fertility and moisture retention properties, which make them better at predicting and multi-crop compatibility.*

Keywords - *Crop Yield Prediction, Internet of Things, Machine Learning, Precision Farming, Soil Information System.*

1. Introduction

Farming is still the main source of livelihood for a large fraction of the rural population of India, but agricultural activities in a large area of the country are rather traditional and labor-intensive. Traditional agriculture in rural India is still dependent on manual labor, rain-fed agriculture, and the passing of agricultural knowledge with minimal usage of modern technology. The small size of land holdings is less than one acre, and this limits the mechanization process and productivity of the land and forces the farmers to rely on family labor or on seasonal labor to carry out planting and harvesting [1]. Moreover, poor irrigation infrastructures, fluctuating rainfall distribution, and rising climatic uncertainty subject agricultural land to ecological stress, thus resulting in variable production and deteriorating soil conditions with time. Although agriculture remains central to the support of the rural population, it is still relatively low in national economic growth. This imbalance implies that technological interventions are required, which can improve productivity without raising the cost of operation or impact on the environment [2, 3]. The shortcomings of traditional farming, including overuse of water and fertilizer, sluggishness in reacting to the loss of soil nutrients, and absence of field-level intelligence, are what drive the shift towards data-oriented and technology-driven agricultural systems.

Precision farming is a shift in the paradigm of agricultural practices, which has generalized to site-specific and data-driven farm management. With the help of IoT sensors, cloud computing, and machine learning, precision agriculture allows monitoring soil and environmental conditions, as well as facilitating informed decision-making at all stages of crop flow [4]. IoT sensors and machines can be used to provide real-time measurements of moisture content in soil, temperature, humidity, light intensity, and nutrient levels, and machine learning algorithms can process these measurements and determine patterns, future yield, and recommend suitable actions. Precision farming, unlike the conventional methods of farming, which involve the use of uniform input application, can optimize the utilization of water, fertilizers, and pesticides according to the real field conditions [5]. Besides minimizing the wastage of resources and production costs, this intervention also improves crop sustainability and health. In third-world economies such as India, where most of the rural population lacks access to high-end agricultural infrastructure, low-cost IoT devices coupled with intelligent analytic solutions offer a scalable mechanism of modernizing agricultural systems in rural regions without compromising economic viability [6].

The Mysuru district falls in the southern region of Karnataka, and it has a varied agricultural topography that can be defined as mixed cropping systems and wide soil types with favorable climatic conditions. The district consists of various taluks having different agricultural practices based on the geography, rainfall, and availability of irrigation. The region is majorly dominated by crops like paddy, sugarcane, ragi, maize, groundnut, and horticultural crops that are aided by soils of the form of red soil, black soil, and alluvial deposits.

The existence of irrigation systems with rivers has shown that moderate rainfall and fertile soils make Mysuru the rightful place to apply and test precision farming technologies. Nevertheless, inter-taluk variability within the district requires local data analysis to be able to effectively determine the level of soil fertility, crop suitability, and yield potential. An informed approach has thus been needed as a result of a data-driven approach that captures regional heterogeneity and enables informed agricultural decision-making on a village level [7, 8].

Despite the fact that the available literature has proven the possibilities of the IoT-based monitoring and machine learning-based prediction of crop yield, numerous of the studies are insufficient and limited in their scope of applicability since most of them do not have their region-specific validation, a limited number of their studies does not involve a comparison between different soils, and a large number of studies do not provide practical decision-support tools that are applicable by farmers.

Specifically, Indian farming settings with rural farming are frequently not represented in large-scale experimental assessments because of the heterogeneous nature of the soil, mix of crops, and the scarcity of resources [9, 10]. These gaps are what propel this work forward, and the framework for this entire precision farming system is very specifically tailored to rural Indian agricultural conditions, with the district of Mysuru, Karnataka, chosen as representative and diverse in terms of agriculture. Among the significant contributions of this research, it is possible to note the creation of a multi-region and farm-specific agricultural dataset of 557 farm-level records developed in several taluks of the Mysuru district, accompanied by 50 benchmark records in neighboring districts. The dataset records an excellent environment, soil, and productivity database, which encompasses temperature, humidity, soil pH, moisture content, nutrient content (N, P, and K) in the soil, light intensity, and yield per acre. This data-based background allows conducting a comparative evaluation of the soil fertility, climatic stability, and crop productivity across areas, which is crucial to measuring the performance of precision farming strategies.

Furthermore, this paper suggests a comprehensive IoT-based design that integrates a multi-sensor hardware device and a Soil Information System (SIS), cloud storage, and a mobile application interface. The suggested architecture enables real-time continuous data gathering, data management, and dissemination of insights to the end users. The system allows the translation of intricate output of analytics generated on the sensor level into information accessible to farmers by linking sensor-level data gathering with cloud-based analytics and mobile access. Analytically, the research contains a systematic comparison of three popular machine learning models, Support Vector Machine, Random Forest, and Decision Tree, for crop yield prediction.

Random Forest model proves to be the best in terms of accuracy and error, and through cut-throat testing with accuracy and error measures, the model proves superior to the other models trained on the Mysuru district data. This finding highlights how ensemble learning strategies are appropriate in dealing with non-linearity and interdependent features of agricultural data. Moreover, the discussion offers empirical data regarding the soil fertility and moisture-retaining properties of the Mysuru district that can be used to explain their effect on the stability of yields and the suitability of multiple crops. Not only do these results confirm the predictive capabilities of the proposed models, but they also demonstrate the agronomic benefits of the area in the case of data-driven farming practice.

Lastly, the work begs practical applicability by providing a mobile-based decision support mechanism that provides actionable alerts and visualization pertaining to the irrigation schedule, fertilizer application, and pest risk. Through explicit connections between findings of the analysis and remedies on the farm level, the proposed framework helps turn the ideal of precision agriculture into more than an analysis-oriented approach to the deliberate active choice.

2. Related Works

The introduction of precision agriculture in recent years has been more dedicated to the combination of Internet of Things (IoT) technologies and Machine Learning (ML) systems to improve crop productivity, resource optimization, and accurate decision-making. Akhter and Sofi [11] explored the precision agriculture systems that integrate IoT-based data collection with machine learning analytics and highlight awareness and technology uptake by farmers. Through their work, they proved the feasibility of the application of ML-predicted diseases in Kashmiri apple orchards and showed the benefits and drawbacks of implementing the IoT and ML solutions in the traditional agricultural setting. A number of studies have been carried out in building a sensor-based hardware platform that is used to provide real-time agricultural monitoring in rural India. Another interesting contribution in [12] was the introduction of a multi-sensor prototype that could measure soil temperature, soil moisture, air temperature, humidity, and gaseous parameters, facilitated by an LCD interface with the farmer.

Farms with the system were able to make real-time decisions about their crops, including wheat, rice, and marigolds, and this proved to have better yields and the use of resources. These investigations highlight the importance of readily available hardware interfaces in reducing the technological divide among rural farmers. On the same note, it has been suggested that IoT-driven weather station systems can be used in the assistance of precision agriculture to automate irrigation, fertilization, and harvesting activities [13]. Sustainable agricultural practices are provided by these systems by using better rural penetration of the internet to facilitate early intervention and optimization of resources.

Smart farming solutions go further to incorporate IoT-based monitoring with data analytics and machine learning to enhance agricultural efficiency. Previous studies have already determined the main smart-farming applications that encompass identifying plant diseases by segmenting images, determining soil properties with the help of optical and moisture sensors, and optimizing the use of fertilizers with the help of the ML model [14]. The combination of these technologies allows managing the input accurately and increasing the yield of crops, especially in such an economy as India, where agriculture is one of the most important areas. Building upon this point of view, in [15], three tiers of smart agriculture architecture that integrated IoT sensors, LoRa-based communication, and data-based analytics were offered.

The system offered information with low latency and low cost on crop health, soil conditions, and weather patterns in a timely manner, which is lower in latency and cost than conventional systems. Some studies have focused on anomaly detection and decision-support applications on smart agricultural monitoring systems. In [16], an IoT-based monitoring system using machine learning and Python-based analytics was introduced, and the anomalies (infestation of pests, lack of nutrients) were identified through classification. This strategy enhanced preemptive intervention, enhanced the stability of yields, and achieved effective resource saving. Equally, to overcome the issue of high latency and limited bandwidth in rural areas, IoT-based smart agriculture systems built on the LoRa-based sensing, fog computing, and cloud architecture have been suggested [17]. These layered architectures leverage the low power consumption and long-range communication characteristics of LoRa to achieve better scalability and reliability of the systems.

Other than environmental monitoring, some other works have also discussed larger smart farming ecosystems and disease detection methods. In [18], comparative works on smart farming models and their effect on the agricultural practice were offered, as well as theoretical frameworks on the diseased fruit and vegetable classification. IoT systems built on Raspberry Pi with camera modules to detect the presence of leaf diseases on various trees have also been explored, and it was demonstrated that it was possible to monitor farms in real-time and even detect diseases in real-time using Wi-Fi-enabled systems [19]. Simultaneously, optimization at the network level has been considered via cross-layer routing and channel access protocols that aim at minimizing delay and enhancing throughput in agricultural Internet of Things networks [20].

The extensive reviews and bibliometrics have also increased awareness of the increasing use of IoT in agriculture and how it is combined with other related technologies, including cloud computing, proximity sensing, and pest detection devices [21]. These papers highlight how IoT can be used to improve the efficiency of production, simplify farming activities, and improve the income of farmers, consequently helping rural areas to develop economically. It has also been suggested that smart soil management systems that involve the use of IoT sensors and cloud-based solutions can be used to decrease the intensity of labor and wastage of fertilizers by continuously measuring soil pH and moisture content [22]. The technological tool of communication is a key to providing accuracy in agriculture in areas that might be geographically adverse. IoT architectures built using LoRaWAN have been discussed to offer reliable and energy-saving connectivity over long distances when traditional networks are not available or not reliable [23].

Developed on the basis of these communication systems, crop recommendation systems with IoT sensors and based on the MQTT protocols of data delivery have proven to be very accurate in crop selection and yield optimization because of the integration of past yield data with current field statuses [24]. Socio-economically, various researchers have noted the plight of Indian farmers because of the lack of irrigation areas, inefficient supply chain, and high transportation rates [25]. IoT-based solutions have also been suggested to deal with the mentioned problems and allow a superior supply-demand management, more efficient irrigation, and new methods of work in agriculture. Bigger studies of interoperability of IoT services and classification have been carried out as well to resolve the compatibility issues in heterogeneous IoT platforms [26].

Precision agriculture has been further extended with low-cost and specialized IoT solutions. Sensor-based environmental monitoring and autonomous platforms, coupled with decision support systems, have been shown to work efficiently in hazardous and remote settings at relatively low cost [27]. Equally, cheap iot and ML-based prototypes with ESP32 controllers and mobile applications are also created to offer real-time monitoring and crop recommendations that focus on the affordability and scalability among smallholder farmers [28]. The research on automation and the minimum human interaction has studied the IoT-based agricultural architecture, including sensors, actuators, networking layers, and wireless technology [29].

Lastly, IoT systems like AGRO-TECH platform are application-specific systems that have been suggested to assist traditional farming by using wireless sensor networks to track soil and environmental conditions and automatically regulate the irrigation system according to threshold conditions [30]. However, the promise of cheap precision farming solutions being used in rural areas has been proven by inexpensive long-range IoT prototypes that can work even without constant internet connectivity and show an improvement in yield of 18-22 percent per year [31].

The available literature indicates that considerable advances have been made in the field of smart and precision agriculture by implementing the methods of IoT and machine learning. Real-time environmental monitoring, automated irrigation, detecting diseases, and crop recommendation have been successfully addressed in terms of many different sensing platforms, communication technologies, and analytical models. Nonetheless, a critical analysis of these publications shows that there are a number of gaps that cannot be filled in, making their applications and generalization limited, especially in the rural Indian farming environment. First, a large number of the existing studies are based on small or region-independent datasets, and in many cases, these experiments are conducted on a controlled or small-scale level.

The unavailability of large region-specific datasets that record the intra-district differences in soil properties, weather conditions, and cultivation procedures limits the effectiveness of yield prediction models once they are implemented in the actual farming conditions. There is also very little comparative analysis within the agricultural regions surrounding them, so it is hard to determine how localized performance and environmental stability of soil affect the model performance and the crop production. Second, it is clear that many IoT-based monitoring systems are proposed, whereas a number of research studies are based on hardware design or communication efficiency without providing a sufficient engagement of end-to-end data analytics and decision-support mechanisms. In most instances, the outputs of the analysis are restricted to dashboards or raw data visualizations and provide only basic actionable advice to farmers. Lack of farmer-oriented feedback systems to convert sensor data and machine learning products into context-relevant, understandable, and timely recommendations also contributes to the lower operational value of these technologies in the field. Third, even though machine learning algorithms like Support Vector Machines, Decision Trees, and ensemble algorithms have been examined separately in terms of agricultural prediction activities, systematic comparative analyses with uniform datasets and performance measures are quite limited. Besides, there is no sufficient study on the correlation between uniformity of soil fertility, environmental stability, and predictive accuracy, especially in areas where there is a mixed system of crops as well as dissimilar land utilization patterns.

Inspired by these shortcomings, the current study seeks to come up with a full-scale precision farming system incorporating localized data aggregation, solid machine learning-based insights, and operational decision-support services. This research uses the Mysuru district as a large-scale representative of agricultural regions in India to merge large-scale field data and comparative regional data to analyze soil fertility, predictability of crop yields, and the robustness of the models. The combination of a Soil Information System, cloud-based analytics, and a mobile application will also guarantee that the insights of the analytical work are directly converted into actionable recommendations that can be applied to the farmers. By so doing, the proposed framework aims to address the knowledge gap between technological advancement and field-scale implementation, which can be added to scalable, data-driven, and sustainable precision agriculture in rural India.

3. Methodology

The proposed precision farming solution is developed as an IoT-based end-to-end system of decision support, uniting real-time collection of data, smart analytics, and user-friendly feedback to farmers. Their architecture, as shown in Figure 1, is a layered architecture with a Soil Data Collection Module, a Soil Information System (SIS), a Data Processing and Analysis layer, cloud-based storage, and a mobile application interface to support decision making. At the field level, several sensors are placed to sense continuously on the primary parameters of the environment and soil surface, such as temperature, humidity, soil moisture, light intensity, and the level of nutrient concentration (N, P, and K). These sensor measurements are sent to the Soil Information System, which is a centralized data storage and initial validation repository.

The SIS guarantees consistent data and offers an interface across the sensing layer and the analytics layer. The processed data will be sent to the Data Processing and Analysis module, where machine learning algorithms are implemented to detect patterns, determine crop yield, and estimate soil fertility. The results of the analyses are saved on a cloud platform, allowing access remotely, trend analysis per history, and scalability. Lastly, analytics are presented in the form of actionable information to the farmer via a mobile application, where warning messages, recommendations, and dashboards are made available to assist in informed decision-making.

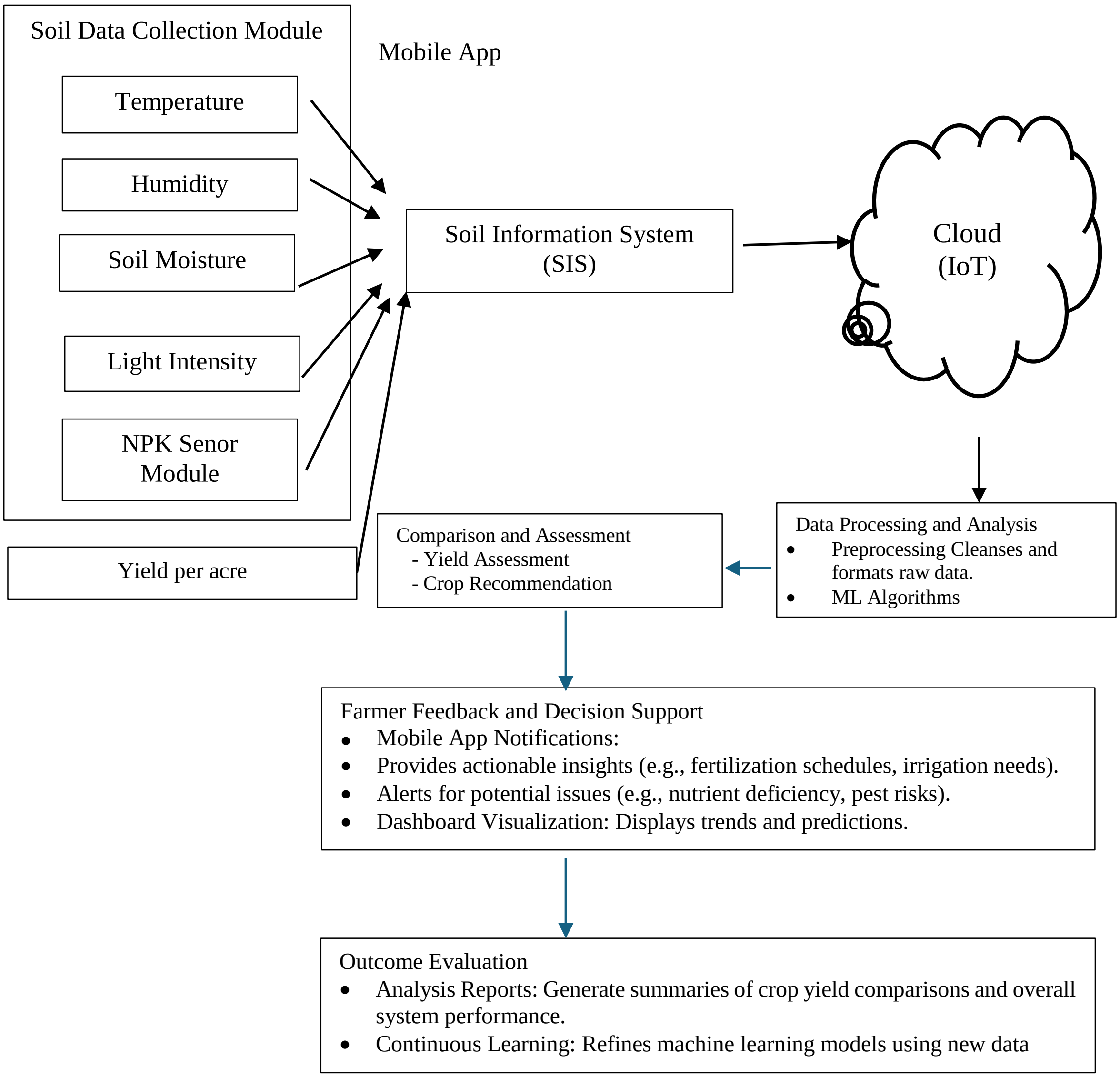

Fig. 1 Proposed Precision Farming Architecture

3.1. Data Collection and Dataset Description

The data utilized in this paper were gathered by means of a large-scale field survey, which was done in seven taluks of the Mysuru district, i.e., Mysuru, Hunsur, Nanjangud, Periyapatna, K.R. Nagar, Srirangapatna, and Saligrama. The total number of farm-level records was 557, which recorded all the agricultural parameters such as village name, taluk, type of crop, temperature (degC), humidity (percentage), pH of the soil, moisture of the soil (percentage), nitrogen (N), phosphorus (P), potassium (K), light intensity (lux), and yield per acre (kg). An additional 50 records were taken in the nearby districts like Bengaluru Rural, Ramanagara, and Tumkur as a way of facilitating a comparative study of the region. This additional data is used as a reference to assess regional changes in soil properties, climate, and crop productivity. The integrated dataset offers a solid basis on which the spatial heterogeneity can be analyzed, and the capability of the given machine learning models to be generalized can be tested. Table 1 gives the description of data collected from farm lands from different Taluks in Mysuru, and Table 2 gives the data collected from neighboring districts of Mysuru. Inspired by these shortcomings, the current study seeks to come up with a full-scale precision farming system incorporating localized data aggregation, solid machine learning-based insights, and operational decision-support services.

3.2. Role of SIS and IoT in Precision Farming

The combination of the IoT technologies and the Soil Information System is one of the main components of the art of making precision farming possible in the suggested system. The IoT sensors that cover the land areas will also enable agricultural areas to monitor the soil and environmental conditions in real time and automatically, without the need to walk around to observe and occasionally sample the soil and environment.

Table 1. Description of Data Collected from Farms Across Various Taluks in Mysuru District

Record ID	Villega Name	Taluk	Crop	Temp (°C)	Humidity (%)	Ph	Soil Moisture (%)	N (mg/kg)	P (mg/kg)	K (mg/kg)	Light Intensity (Lux)	Yield per Acre (Kg)
1	Adakamaranahalli	Mysuru	Rice	30	75	6.8	45	120	30	50	8000	1200
2	Ankanahalli	Hunsur	Maize	32	65	7.2	40	130	35	60	8500	1500
3	Banur	Nanjangud	Sugarcane	34	70	7.0	50	150	40	70	7000	1800
4	Belakavadi	Periyapatna	Cotton	33	80	6.9	55	140	45	65	7500	1100
5	Bhogadi	K.R. Nagar	Wheat	28	60	7.1	35	110	25	45	6000	1100
6	Channarayapatna	Mysuru	Rice	31	78	7.1	42	120	30	55	8200	1300
…												
…												
556	Hanumantha Nagara	Saligrama	Cotton	46	34	6.9	64	32	74	24	550	1150
557	Moodalabidu	Saligrama	Maize	62	41	6.8	71	33	78	26	640	1480

Table 2. Description of Data Collected From Farms Across Neighboring Districts to Mysuru

Record ID	Village Name	District	Crop Type	Temp (°C)	Humidity (%)	pH	Soil Moisture (%)	N (mg/kg)	P (mg/kg)	K (mg/kg)	Light Intensity (Lux)	Yield per Acre (Kg)
1	Magadi	Tumkur	Maize	32.0	61	6.3	21.0	51	21	235	56257	1269
2	Hosakote	Tumkur	Tomato	30.0	78	6.1	33.0	35	23	213	55179	925
3	Nelamangala	Tumkur	Groundnut	33.8	62	6.1	34.0	48	30	175	49249	987
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47	Doddaballapur	Bengaluru	Paddy	28.2	70	6.9	27.4	42	31	192	49542	1043
48	Tumkur	Tumkur	Beans	29.8	64	6.5	22.0	40	25	208	50893	1125
49	Kanakapura	Ramanagara	Maize	31.4	65	6.4	24.2	55	20	217	52215	1235
50	Anekal	Bengaluru	Tomato	29.0	66	6.6	20.5	43	27	209	50984	1168

The transmission of data obtained by heterogeneous sensors is provided by wireless communication technologies (Wi-Fi, LoRa, or Zigbee) based on the limitations of deployment and the availability of connectivity.

The Soil Information System has been spread as a middleware level, coordinates sensor values, preliminary inspection, and prepares data to be subsequently used in analytics. The SIS ensures historical analysis, detection of trends, and constant updating of the models by keeping the records well-organized and with time stamps. This form of integration allows a farmer to achieve precision farming activities like automated scheduling of irrigation, optimal application of fertilizers, and early warning of unfavorable conditions, which gives a better use of resources and lowers the operational expenses.

3.3. Data Preprocessing and Feature Engineering

Raw sensor data are also always vulnerable to noise, missing data, and inconsistencies in the scale that can negatively impact the machine learning performance. Thus, an extensive preprocessing chain of data was used before training the model. Data gaps were addressed through statistical imputation methods, in which the gaps of sensor readings were addressed using representative values of observed data.

$$x' = \frac{1}{n}\sum_{i=1}^{n} x_i \quad (1)$$

Normalization was done by use of the z-score transformation so that the contribution of features is homogeneous. The Interquartile Range (IQR) and Z-score were applied to isolate outliers and eliminate them in order to avoid the bias of learning. After preprocessing, the features of temperature, humidity, soil pH, moisture, and nutrient levels were identified depending on their agronomic importance. Also, the derived Soil Fertility Index (SFI) was calculated by weighted aggregation of N, P, and K values.

$$SFI = w_n N + w_p P + w_k K \quad (2)$$

Crop yield prediction was done using three supervised machine learning algorithms, which were Support Vector Machine (SVM), Random Forest (RF), and Decision Tree (DT). These models were chosen because they have been found to be effective in dealing with non-linear equations as well as mixed-type agricultural data. An SVM model is a regression model that attempts to find an optimal regression equation that has the least error in prediction. Random Forest is an ensemble learning method that builds a set of decision trees based on the bootstrap sampling and aggregates their output in order to enhance durability and decrease overfitting. Decision Trees divide the feature space recursively using impurity minimization measures, including Gini index or entropy, and give decision rules that are interpretable to estimate the yield.

The last level of the proposed framework is aimed at providing analytical results to the farmers in a practical and easy-to-understand way. A mobile application interface would give real-time notifications on irrigation requirements, fertilizer timing, and possible pest threats in the case of sensor logs and machine learning forecasts. The trends in soil fertility, environmental conditions, and the yield are shown in the visual dashboards to allow farmers to track the farm performance over time. This is a feedback loop feedback mechanism that makes continuous learning and adaptation as new field data is periodically introduced to enable the prediction model to be refined. The system involves direct connection of the analytical intelligence to the field-level actions, which enables precision farming to be not a passive monitoring, but rather a farm management that is proactive and data-driven.

3.4. Mathematical Formulation of Irrigation and Fertilization Scheduling

To ensure methodological rigor, irrigation and fertilization scheduling are governed by quantitative threshold-based decision logic integrated with predictive analytics. Irrigation is triggered when the measured soil moisture SM_t falls below the crop-specific lower bound $SM_{min}^{(c)}$, adjusted by an evapotranspiration factor $ET_t = \alpha T_t + \beta H_t$. The irrigation decision function is defined as $I_t = 1$ if $SM_t < SM_{min}^{(c)} - \gamma ET_t$, and $I_t = 0$ otherwise. The recommended irrigation quantity is proportional to the moisture deficit, expressed as $Q_t = k(SM_{opt}^{(c)} - SM_t)$. Fertilization scheduling is determined using a Soil Fertility Index (SFI), computed as a weighted normalized aggregation of nutrient concentrations: $SFI_t = w_1 \frac{N_t}{N_{req}^{(c)}} + w_2 \frac{P_t}{P_{req}^{(c)}} + w_3 \frac{K_t}{K_{req}^{(c)}}$, where $w_1 + w_2 + w_3 = 1$. Fertilization is recommended when $SFI_t < \theta$, indicating nutrient deficiency relative to crop-specific requirements. In the current implementation, these decision variables generate advisory outputs delivered through the mobile application for manual execution, while the framework remains extensible for future actuator-based automation.

3.5. Mobile Application and Actionable Insight Module

Besides real-time sensing and predictive analytics, the proposed precision farming architecture integrates a mobile-based decision-support system that converts analytical outputs into field-level recommendations. Figure 2 presents the mobile app dashboard designed. The mobile application is the last level of interaction between the system and farmers and will make sure that the insights produced by the IoT sensors and machine learning models are available in a practical and user-friendly way. The application also updates the cloud analytics server and obtains analyzed data, projections, and assessments of soil conditions in real time.

The system risks actionable information in three main areas, which include irrigation control, detection of nutrient deficiencies, and pest threat. The irrigation advisories are obtained through the continuous comparisons of the soil moisture readings with the crop-specific optimal readings. In cases where water content drops below the recommended range in relation to agronomical aspects, the system sends irrigation warnings in time, giving the relevant schedules. The concentration of nitrogen, phosphorus, and potassium is analyzed to give a notification of nutrient deficiency, as well as their input to the calculated Soil Fertility Index. In case irregularities in the recommended levels of nutrients are observed, the application gives specific fertilizer suggestions based on the type of crops and the soil status.

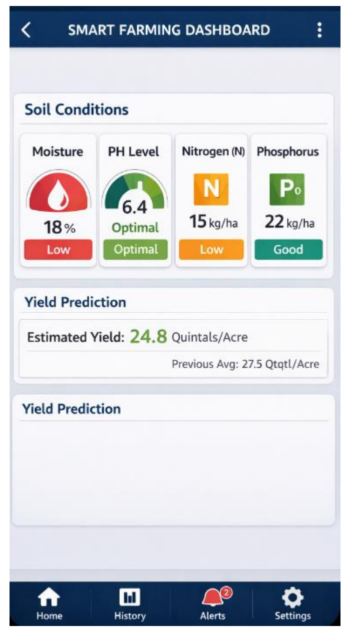

Fig. 2 Mobile App Dashboard Design

The pest risk alerts are produced via a set of rules-based evaluations considering the environmental parameters like temperature, humidity, and the category of crops. There are some climatic ratios that support the growth of pests, which generate early warning messages, connecting preventive actions instead of corrective actions. Moreover, the predictive model of the Random Forest is associated with the analysis of the importance of features to determine the major agronomic stress factors influencing yield. In case of a decrease in predicted yield, the system compares among the most effective contributing features, e.g., nitrogen deficiency or inadequate soil moisture, and converts the results into particular agronomic advice.

The farmer-facing mobile application is designed as a cloud-connected decision-support interface that retrieves processed sensor data and predictive outputs from the Soil Information System through secure API communication. The notification system operates using event-based triggers derived from irrigation, fertilization, and pest-risk thresholds. When predefined conditions are satisfied, the application generates categorized alerts with timestamped recommendations specifying required actions. The dashboard is structured into modular sections displaying real-time soil parameters, nutrient status relative to crop-specific standards, predicted yield values, and historical trend graphs. Visual elements such as color-coded indicators, bar representations, and time-series plots are used to simplify the interpretation of moisture levels, Soil Fertility Index variations, and environmental patterns. This implementation ensures that analytical outputs are transformed into structured, easily interpretable information that supports informed decision-making at the farm level.

4. Results and Discussion

The experimental analysis was based on the agricultural data, which was gathered in 557 farms in 7 taluks of Mysuru district and 50 farms in the adjacent districts, that is, Bengaluru Rural, Ramanagara, and Tumkur. The spatial heterogeneity of the data made it possible to study the effects of the soil properties and the environmental factors on the crop productivity on the in-district and inter-district scales. The relative stability of the climatic conditions and the indicators of soil fertility in the Mysuru district farms are relatively stable as compared with the rest of the areas, as they are summarized in Tables 1 and 2.

The values of pH in the soils of Mysuru taluks were highly concentrated in the neutral range (mean=6.8), which is well known as the best condition of nutrient availability and multiplexing of crops. On the contrary, similar districts experienced fairly acidic soil conditions (mean pH=6.3), which can inhibit nutrient absorption and cause an excess reliance on external sources of fertilizers. Such a regional difference will give a significant basis to understand the predictive performance of machine learning models, which is explained further.

Correlation analysis of the Mysuru data was carried out to determine the quantitative relationship between soil and environmental parameters and their effect on yield. The findings indicated that there was a positive correlation with the variables of nutrients in the yield of crops, specifically with nitrogen ($r \approx 0.72$), potassium ($r \approx 0.69$), and soil moisture ($r \approx 0.65$). These results verify that nutrient availability and moisture retention can be important in agronomics with regard to crop productivity. There are also moderate positive relationships between yield and temperature ($r \approx 0.48$) and light intensity ($r \approx 0.44$), indicating that the climatic stability plays a role in the increase in yields when it is coupled with suitable soil conditions. The soil pH showed a non-linear correlation with yield, with the values near neutrality showing a higher productivity and the deviations from neutrality decreasing the yield stability. The relatively lower correlation ratios found in adjacent district data indicate greater environmental variability and reduced homogeneous soil fertility, which have a negative influence on the prediction of yields.

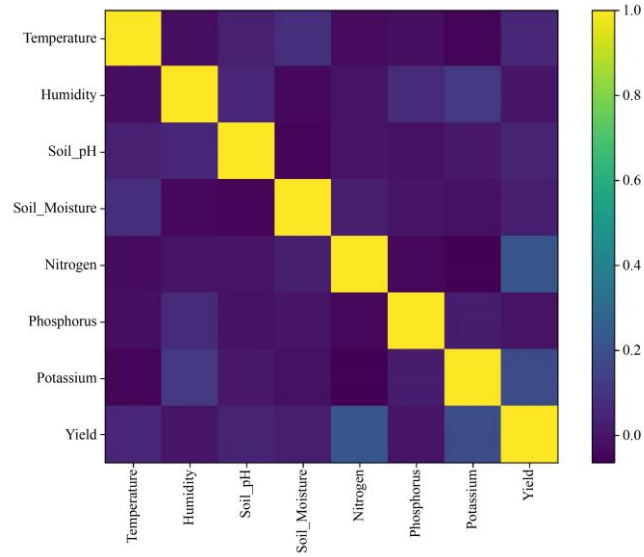

Fig. 3 Correlation Heatmap of Soil Parameters and Yield

The correlation heatmap (Figure 3) demonstrates the direction and strength of the correlation between the important soil, environmental parameters, and crop yield. The correlation of yield with both nitrogen and potassium is very high, with a positive value, meaning that the availability of nutrients is the major factor that determines crop productivity. There is also a moderate positive correlation between soil moisture and yield, indicating the need to have sufficient water in the soil to maintain the growth of plants. Temperature and humidity show lower correlations with yield, indicating that climatic factors play a second-hand role in conditions that are relatively stable in the region of study. The pH of soil exhibits a low direct relationship, which denotes that the yield advantages take a peak at an ideal pH scale and not in a linear manner. The plot, in general, substantiates that the most influential factors of the yield are the soil nutrient balance and moisture, which proves the high-performance of soil-oriented machine learning models in this study.

In a bid to envisage the contribution of the individual parameter in predicting the yield, the feature importance analysis by use of the Random Forest model was achieved using the Mysuru dataset. The findings show that nitrogen content was found to be the most influential one since it predicted the overall predictive value by about 26 percent. Potassium and soil moisture are the next most important, with scores of 21% and 18, respectively. Phosphorus and soil pH had a moderate impact, whereas temperature, humidity, and light intensity had a lower, but still significant, value of importance. The sequence of feature significance is quite consistent with the concepts of agronomy, which supports the idea that nutrient proportions and moisture conditions are the leading factors that determine yield in Mysuru mixed cropping regimes. The fact that the relative significance of the climatic variables was low indicates that Mysuru is relatively lucky to experience relatively constant weather conditions, which means that soil-related variables will be more significant in determining the yield. Conversely, the importance distribution in the feature importance analysis performed on the neighboring district data was more dispersed, and therefore uncertain, and less confident in the model since the data varied among the environments.

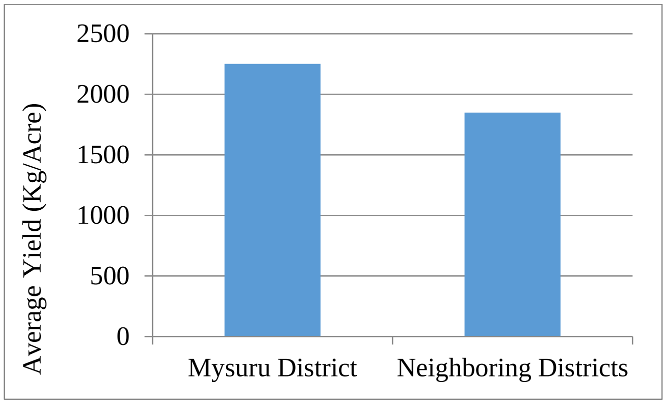

Fig. 4 Average Yield Comparison Across Regions

It is observed that a comparative analysis of the yield per acre shows that Mysuru district has a performance deficit as compared to its neighbors. The average yield in the Mysuru farms was about 2,200 kg/acre, as compared to the average yield of neighboring districts, which was about 1,850 kg/acre, as shown in Figure 4. This is statistically significant and observed to be consistent with various types of crops. The improved Mysuru yield performance could be explained by a set of conditions, such as even and balanced soil pH, increased and more consistent NPK levels, as well as better-retained moisture. These traits minimize crop stresses and permit them to attain an efficient nutrient uptake, which leads to increased yields and decreased diversity among crops. The neighboring districts, on the other hand, showed more variation in the soil moisture and the nutrient content, resulting in unreliable productivity and vulnerability to climatic stress.

Accuracy, Mean Absolute Error (MAE), and Root Mean Square Error (RMSE) were used as a summary of performance in assessing predictive performance of the three machine learning models, which are: SVM, Random Forest, and Decision Tree, as summarized in Table 3. The Random Forest model was the best model to evaluate, with an accuracy of 95.7 in the Mysuru dataset, the lowest MAE (96 kg/acre) and RMSE (121 kg/acre). The excellent work of Random Forest can be explained by its ensemble form, which is able to describe non-linear relationships and interactions between soil and environmental variables and minimizes overfitting.

The interpretable models, like the Decision Tree models, had higher error rates because they were sensitive to noise and data partitioning. SVM was found to be competitive in performance but less resilient to mixed agricultural data that had application of different distributions. It is important to note that in all models, there was a decrease in accuracy with an increase in error in training on nearby data in the district, a fact that proves the point that increased environmental variability negatively impacts model generalization. The observation further supports the relevance of region-specific information and model calibration on local scales during precision agriculture tasks.

Table 3. Description of Data Collected from Farms

Model	Region	Accuracy (%)	MAE (kg/acre)	RMSE (kg/acre)
Support Vector Machine (SVM)	Mysuru District	92.3	108	134
Support Vector Machine (SVM)	Neighboring Districts	87.1	132	158
Random Forest (RF)	Mysuru District	**95.7**	**96**	**121**
Random Forest (RF)	Neighboring Districts	89.6	125	144
Decision Tree (DT)	Mysuru District	91.5	112	139
Decision Tree (DT)	Neighboring Districts	85.4	138	162

The feature importance plot (Figure 5) of the Random Forest model reveals the amount of contribution made by each input parameter to crop yield prediction. Nitrogen appears to be the most significant characteristic, which means that this element is crucial to plant growth and biomass development. The next contributors are soil moisture and potassium, covering the combined significance of sufficient water and nutrient levels in the realization of better yields. Phosphorus and pH of soil have moderate effects, which represent their effects on root growth and nutrient uptake at optimum levels. Contrary to that, temperature and humidity have lower scores on the importance scale, indicating that the influence of climatic variables on yield prediction in the area of the research is rather low, because of rather steady weather conditions. All in all, the plot proves that the parameters regarding soil control the yield determination, which confirms the efficiency of the Random Forest model in terms of its use in precision farming.

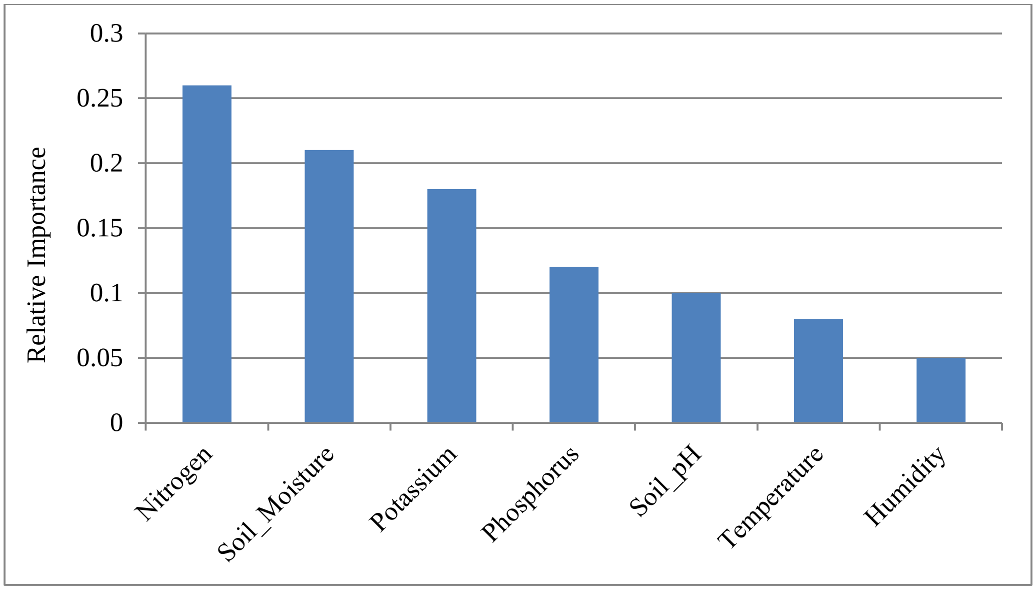

Fig. 5 Feature Importance Plot

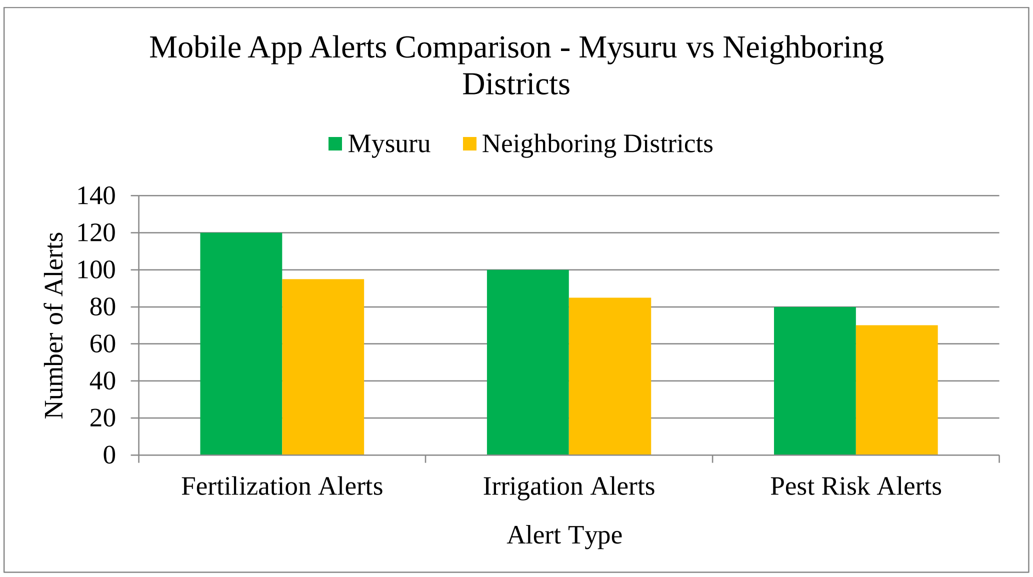

Fig. 6 Actionable Insights and Alerts

In addition to the predictive accuracy, the effectiveness of the proposed system was measured by its ability to provide actionable insights to farmers. As shown in Figure 6, there was an increased frequency of irrigation, fertilization, and pest-risk notifications in the mobile application in Mysuru farms than in the neighboring areas. The result is indicative of the more robust and informed data trends that the IoT sensors in Mysuru have recorded, and thus, are able to make timely and context-sensitive suggestions. The farmers also had real-time alerts on soil moisture levels, nutrient deficits, and future pest attacks, which could be informed and dealt with, rather than corrected. The combination of predictive analytics and mobile-based decision support turned raw sensor data into actionable advice, therefore improving the usefulness of the system in place and fostering sustainable farm management.

These findings clearly show that the Mysuru district has desirable soil fertility and climatic conditions and predictability in yield as compared to other agricultural areas. Statistical correlation and feature importance tests prove that nutrient availability and soil moisture are the key determinants of yield, and machine learning testing demonstrates the strength of the ensemble-based method, including Random Forest. The implication of the effective data analytics, forecasting, and farmer-centric decision support, the proposed IoT-ML framework proves its relevance to be deployed in rural Indian agriculture.

5. Conclusion

This paper introduced a combined IoT and machine learning-based precision farming system that could operate under the conditions of rural Indian agriculture, and the Mysuru district was the representative test area. The proposed system proved the efficiency of integrating real-time soil and environmental sensing with data-driven analytics, which is based on gathering and examining a vast amount of data regarding 557 records of farm-levels in Mysuru and 50 benchmark records in the neighboring districts. The statistical correlation analysis and the results of the feature importance of the Random Forest showed that the soil-related parameters (especially nitrogen, potassium, and soil moisture) are the most important factors in crop yield, and the secondary causes are climatic factors in constant regional conditions. The comparative analysis of machine learning models indicated that the Random Forest algorithm produced the highest predictive accuracy (95.7) and the lowest error indicators with respect to the Mysuru dataset, and thus beat other models of SVM and DT. These results bring out the benefits of ensemble learning to manage non-linear relationships and non-homogeneous agricultural data. Additionally, a mobile-based decision support system was implemented to convert the findings of the analysis into actionable recommendations, which will help farmers to make timely and informed decisions about irrigation, fertilizer, and pest control.

The proposed framework can be expanded to future work to use larger and more varied datasets across the various agro-climatic zones to boost the generalization and scalability of the model. Application of deep learning, i.e., recurrent or hybrid ensemble models, can also enhance yield prediction accuracy of the system, especially in the highly dynamic environmental factors. The policy-driven adoption of data-driven precision farming solutions in India can be deployed on a large scale through collaboration with agricultural research institutions and government agencies, and long-term sustainability.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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