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Article

A Sensor-Driven Mobile Decision-Support System for Soil Fertility Advisory and Recommendation

Farhat Shaikh[1*], Satish Sankaye[2]

[1]Department of Computer Science and IT, Dr. G. Y. Pathrikar College, MGM University, Chhatrapati Sambhajinagar, Maharashtra, India.
Email: farhatshaikh1091@gmail.com
[2]Department of Computer Science and IT, Dr. G. Y. Pathrikar College, MGM University, Chhatrapati Sambhajinagar, Maharashtra, India.
Email: sankaye.satish10@gmail.com

Abstract: Soil fertility assessment is required for field-level agricultural decision-making. Raw readings from soil sensors can be unintuitive or ambiguous to farmers. Nitrogen, phosphorus, potassium, pH, electrical conductivity, and moisture parameters require semantic translation into recommendations for crop selection, fertilizer planning, and soil amendments/management. This paper describes a mobile decision-support system for semantic soil fertility advice and recommendations via a developed Android-based prototype. Soil sensor data from the Internet of Things are coupled with a pre-trained fertility prediction layer to generate a categorical output of low/medium/high fertility conditions. The predicted fertility is then passed onto an advisory layer, which automatically generates recommendations for stakeholders. The prototype graphical user interface includes location selection, displaying soil test information, displaying fertility status, NPK advice, pH advice, EC advice, moisture advice, crop recommendations, fertilizer recommendations, fertilizer quantity recommendations, water quality advice, and government resources. Validation of the study was performed by ensuring model-app output consistency, testing L/M/H advisory cases, and ensuring workflow via screenshots. Results indicate that soil sensor data can be processed within one mobile workflow to generate easily interpretable fertility status, advisory alerts, and recommendations. This study investigated and validated an Android-based decision-support tool that can translate sensor-derived soil information into farmer advice. Limitations of this study include prototype-level validation, not a fully deployed commercial tool.
Keywords: digital agriculture; farm-input estimation; field usability; mobile decision support; nutrient interpretation; recommendation engine.

1. Introduction

The timely and specific decisions related to soil characteristics, nutrient status, irrigation schedules, fertilizer use, and crop planning have now become important aspects for managing agricultural crops. In India this problem is acute, especially in the states like Maharashtra, since the district-wise local soil condition, cropping pattern, irrigation source, rainfall characteristics, and climatic conditions are vastly different from one district to another. So, a typical recommendation that may be applicable to the entire state cannot be prescribed to all the districts in the same measure; hence, it necessitates making local decisions for effective crop management based on the local characteristics. As we have recently seen some research on machine learning, which proved it may be helpful to achieve agricultural sustainability by focusing on a critical concept for local decision support for better agricultural outcomes in the context of Maharashtra [1]. Hence, any practical soil advisory system that relies on sensor data will need to obtain input values from the user or sensor devices and present the information in a simple and understandable manner. In smart agriculture over the years many developments have taken place, such as IoT sensors, low-cost monitoring devices, cloud-based data management, and analysis using machine learning. This is helping in acquiring a multiple times greater number of field and soil attributes, like pH, soil moisture, NPK value of soil, soil temp, etc. This method offers advantages over the traditional approach to soil testing [2]-[6]. Sensor-based systems offer real-time information about soil parameters and comparatively quick return of information. But just getting data from sensors does not really solve farmers' problem; the information collected through sensors should be interpreted and effectively disseminated to reach the targeted audience. In the recent era, the challenge evolved from sensing/predicting the information to turning the interpreted information into actionable advice that farmers can effectively act upon.

The topic has much significance, as the fertility of the soil plays an important role in it. Some basic facts about soil fertility include nitrogen, phosphorus, potassium, pH, electrical conductivity, moisture content, and others that are fundamental information that, although scientifically proven, may be difficult for a layman to grasp. For example, getting a nitrogen value from the sensor might not immediately tell the farmer if soil has been adequately supplemented, whether additional amendments are necessary, or the need for monitoring soil properties on a frequent basis. Recent articles highlighted the advances that have been made in IoT sensor technology, AI-based nutrient value calculation, crop prediction, water management & smart farming systems. However, in most cases, the approach has focused on individual components like sensing, predicting, or monitoring. Most systems do not comprehensively use sensor input to provide advice on fertility state assessment, soil attribute interpretation, crop recommendations, fertilizer recommendations (including amount estimation), irrigation advisories (including quality advice), and governmental scheme information for application. The research gap that this study aims to address is more in terms of translating sensor-driven soil information into a simple, coherent, and understandable advisory for the farmer. A truly functional system must provide the option of location selection, display input data, report the current soil fertility condition, generate advisories for specific parameters, recommend crops and fertilizers with appropriate quantity estimation, offer a water-quality interpretation, and link to governmental initiatives through a simple-to-operate Android interface. Despite many works highlighting specific modules and advancements in the respective areas of interest, many practical aspects such as reliability of sensors, connectivity issues, the cost of such solutions, and difficulty of usage have often resulted in their slow or limited adoption in the field [2], [4], [5], [9]. Therefore, a successful smart system must also consider user-friendliness, usability, advisory value, and adoptability issues. Motivated by the above limitations of the current systems. In this study, we propose a sensor-driven mobile decision support system for the soil fertility advice and recommendations on an Android platform.

The system, being a research prototype, will incorporate an ensemble-based trained model for estimating the current soil condition to categorize it into three basic levels, low, medium, and high, using inputs such as N ppm, P ppm, K ppm, pH, EC dS/m, moisture VWC%, and region. Fertilizer Status. Then this output grade is fed to a specific advisory layer to process the advice and recommendations. This Android prototype has the functional workflow comprising a few modules such as Select Location, Display Soil Data, Display Fertility Status, Advisories (NPK, pH, EC, Moisture, Water Quality), Recommendations (Crops, Fertilizers), Fertilizer Calculator, Government Resources links, etc. Each of these modules will guide users through logical steps, from understanding to decision-making and implementation, using sensor-driven information via a user-friendly application. Therefore, the study is to present an Android-based user framework by processing the sensor data to generate simple, comprehensive, and timely agricultural advisories for supporting soil management. The validation of the prototypes emphasizes consistency between input, output, and user interfaces; the validity of LLW/MD/HI advisory scenarios; the validation of the operational workflow using screenshots; and the evaluation of the practical usage of the system in the agricultural field. This validation process is designed to demonstrate that the soil information and its transformation into advice, according to the system workflow and its interconnected modules, provide comprehensive end-to-end solutions. The work does not claim that the prototype is ready for field deployment for large-scale use or commercialization. Rather, it aims to provide a proof-of-concept demonstration in the framework of research.

2. Literature Review

Recent advances in digital agriculture have encouraged the use of connected sensing systems to observe soil and field conditions more continuously than conventional testing approaches. Across Indian farming contexts, IoT-based platforms are being used to capture variables such as pH, moisture, temperature, electrical conductivity, and nutrient-related measurements so that decisions can be made with less delay and greater field relevance. Yet the main research challenge has now shifted beyond data capture itself. The more important issue is how these measurements are transformed into simple, trustworthy, and actionable guidance for farmers. A large share of current studies emphasizes hardware setup, monitoring frameworks, or predictive analytics, whereas fewer works show how soil observations can be integrated into a practical Android advisory application that supports local data access, fertility understanding, recommendation delivery, and ease of use in real field conditions. Existing literature also continues to note barriers such as sensor inconsistency, network dependence, cost sensitivity, and adoption-related usability issues, indicating that practical deployment remains an open area for improvement [2]–[6].

Kumar et al. (2025) developed an IoT-based smart farming system that integrates several sensors and automated monitoring for real-time agricultural decisions. Their investigation indicates that connected sensors in the field make for more precise, practical data collection. The system informs about soil fertility, but it doesn’t have a specific mobile component that allows users to fully dig into fertility classes or view soil conditions when planning fertilizer use. So, while it does deliver useful information and is an excellent example of smart agriculture, it doesn’t quite cut the mustard as a full-featured soil-fertility advising tool [2]. Kalaivani et al. (2025)

built an IoT-enabled soil and crop monitoring using affordable sensors for precision agriculture. This work is significant in India, as it focuses on affordable monitoring, which is essential in practical settings. On the other hand, their work focuses on the sensing and monitoring architecture, rather than transforming soil data into an end-to-end advising system. The proposed solution indicates that cheap field monitoring is feasible, but the way to represent and analyze the soil data, as well as how to translate it into useful advice and make it accessible to farmers on an Android-based interface, remains an issue [3]. Gupta et al. (2025) have also shown smart agriculture using IoT to achieve automated irrigation and water resource management along with prediction. This work adds evidence for the use of real-time sensing and automated decision-making support in farming in terms of irrigation efficiency and optimal utilization of resources, although the application here is not focused on soil fertility interpretation in particular. Thus, the work is within the realm of smart agriculture but doesn't contribute directly to translating soil features into a farmer-understandable fertility advising pipeline with explanations and quantity planning [6]. Sharafat et al. (2025) paper represents a move toward a more practical approach to real-time agricultural intelligence and integrated sensor-driven analytics. However, the scope of the work is crop prediction rather than fertility advisory. Hence, the contribution is to the larger trend of mobile- and IoT-based agricultural decision systems, rather than to specifically showing soil-fertility conditions, recommendation logic, and farmer-understandable support in a specific Android advisory flow [8]. Dinn et al. (2025) commented on the improvement of soil management using IoT sensors and acknowledged the increased integration of sensors in the decision-making process on the soil. This is a very useful contribution, as it is the only paper among the selected references to specifically tackle the concept of sensor technology in the soil; in other words, the contribution synthesizes the role of sensors in monitoring pH, soil moisture, NPK, etc. On the other hand, the paper also points out ongoing limitations concerning sensor accuracy, connectivity, and scalability, which are of vital importance when it comes to building confidence on field observations and, hence, on the advice given to the users on the basis of these observations. This is to say that the contribution corroborates the importance of sensor technology in the soil but also implies the need for better integration between the reliability of sensing and its interpretation for an advisory system [10]. Eyasin et al. (2025) suggested Crop Synergy, which is an IoT-based framework for smart and sustainable crop management. This suggests an ongoing effort toward an integrated digital agricultural system that combines sensing, communication, and a decision system based on cloud information. Nevertheless, the system deals with a scope wider than soil fertility, and no specific mobile prototype has been built for displaying the status and for assisting with the soil-fertility recommendation part. This article indicates an increasing trend toward intelligent agriculture and offers starting points for designing a soil-fertility advisory system and its practical usability in the field [11]. A survey by Sreeram et al. (2025) on soil moisture sensing technologies in smart agriculture showed that monitoring quality remains the primary issue during deployment in the field. This is relevant in this context as it highlights that sensing devices have to contend with calibration issues, communication, and environmental diversity before a practical farm-ready smart farming solution can exist. This is pertinent to this work, as the mobile advisory prototype needs not only to present the findings but also to rely on the sensing and analysis system to make sense in real field variations. Hence, the paper supports the point that smart agriculture is far from a "closed research problem" when it is viewed from a lens that combines deployment robustness and advisory usability [12]. In the mobile decision-support direction, Sharma et al. (2025) developed FertiCal-P, an Android-based decision support system to provide fertilizer recommendations based on measured soil macronutrients and pH. The work is important as it shows that soil-test-based recommendation support can indeed be delivered using a mobile platform. On the other hand, FertiCal-P acts as a calculator which uses soil-test values and provides a fertilizer value. The current work, however, aims at a richer advisory prototype which provides location-based soil data access, allows the user to view soil parameters, shows the fertility status, offers recommendation support, and provides fertilizer quantities all within a seamless workflow. Hence the current work provides support for the feasibility of Android-based decision support but indicates that there is scope for more rich soil-advisory prototypes [13].

3. Research Gap

Research in smart agriculture has made significant progress in the use of IoT sensors, machine learning algorithms, mobile applications, and cloud-based solutions for monitoring and decision support of farming activities. Many research articles showed the feasibility and performance of sensor-based systems in obtaining soil properties and weather parameters like nitrogen, potassium, and phosphorus (N, P, and K), pH, EC, moisture, temperature, and weather attributes and using them to infer or decide on crops or field management aspects [2]–[8]. While such studies suggest that smart agriculture has reached the technical feasibility stage, existing literature generally suggests the partitioning of functions like sensing, prediction, monitoring, and advisory as independent modules rather than forming a united decision support flow.

In this manner, the separation of sensor readings and their subsequent advisories form a practical gap within soil fertility management. N, P, K, pH, EC, and moisture obtained from soil sensors might be statistically sound, but it requires an appropriate advisories layer to translate these numbers into intelligible forms. A mobile application that simply displays N, P, and K values thus has many gaps. A mobile application that only categorizes the current fertility status as low, medium, or high will have limited utility without the corresponding parameter-wise explanations and a comprehensive set of fertilizer advice, crop and water management guidance, and financial tools. Another practical gap highlighted through the literature review on smart agriculture systems is the absence of end-to-end validation for mobile advisories. Several publications highlight results on sensor performance, prediction modeling outcomes, monitoring designs, or cloud architecture for agricultural purposes, but very few describe how sensor input values trace through intermediate decision support levels to final mobile advisory interfaces. For a smart decision-support system, it is essential that the outputs of one stage follow logic and structure for the inputs of subsequent stages. This process of tracing shows how sensor-derived values are translated through to mobile displays. It is required that the advisories produced should logically flow from sensor data.

Furthermore, it is imperative to examine the agreement of the prediction results rendered by the mobile application vis-à-vis the backend prediction layer. Numerous prototypes show screenshots, but they usually do not explicitly verify the alignment between the back-end fertility prediction logic and the Android screen. For a mobile soil advisory, consistency is key since any advised fertilizer quantity, nutrient allocation, and crop recommendations will heavily depend on the fertility grades presented to the end-users. Therefore, this research will investigate the consistency of mobile application outputs based on existing prediction models. Moreover, advice from a mobile application needs to be adaptive to different levels of fertility. For a fertility status of 'low,' 'medium,' or 'high,' advisory guidelines will differ. Typically, for 'low' soil fertility, corrective strategies should be recommended, while 'medium' fertility needs suggestions for optimum input utilization with monitoring, and 'high' fertility should suggest best practices towards maintenance-level recommendations. Another research gap is the lack of explicit validation on how advisories respond to variations in soil fertility levels.

In the present study, we will develop and validate an Android mobile-based decision support application that uses sensor-based data to assess soil fertility. In this study, we will employ IoT sensors to harvest soil parameters and will use an ensemble-based prediction model to classify soil condition into 'low,' 'medium,' and 'high' fertility categories. The predicted fertility grades will then be translated by an advising logic engine into parameter-wise interpretations and advisories that will include information on NPK requirements and P and K soil requirements. Soil pH-advised level, soil moisture advisories, crop-recommended practices, quantity recommendations, nutrient management advice, crop selection recommendations, advisories on the quality of irrigation water, and information on accessing available government schemes. All this information will be made available within an Android application workflow.

The core contribution of this work lies in not just developing an interface for an Android mobile application but in providing proof-of-concept evidence of an end-to-end decision support system where various sensor-driven data inputs are processed and translated to a logical progression of fertility estimations, interpretations, advisories, and recommendations for soil fertility management and practical farmer-friendly recommendations. This study addresses the research gap by creating and demonstrating a comprehensive decision support workflow for mobile soil fertility advisory systems, which includes sensor inputs, predictive modeling, consistent outputs, accurate advisories, and appropriate visualization on Android devices.

4. Proposed Mobile Decision-Support Framework

The proposed system is designed as a sensor-driven mobile decision-support framework for soil fertility advisories and recommendations. The main goal of the framework is to turn soil sensor readings into useful advice that can be easily seen and understood using an Android app. Instead of treating the mobile application only as a display interface, the system is structured as a connected workflow in which soil data, fertility interpretation, advisory logic, and farmer-facing recommendation modules work together. Soil-related input attributes: Our system starts by taking soil attributes, which come from sensor readings. Such attributes are nitrogen, potassium, phosphorus, pH, electrical conductivity (EC), moisture, region, and fertilizer status. Each attribute has a distinct function in the interpretation to produce an advisory, i.e., nitrogen, phosphorus, and potassium help in interpreting the nutrient status of soil; pH in soil acidity and alkalinity; EC helps in determining the salinity; moisture helps in water supply/irrigation support, while region and fertilizer status are supporting attributes that help to visualize and interpret the soil reading history in a particular view. After the soil input values are received, they are passed to a pre-trained ensemble-based fertility prediction layer. This layer classifies the soil condition into one of three fertility grades: Low, Medium, or High. The internal algorithmic development of the prediction layer is outside the main scope of this paper.

The present study employs the prediction layer as a functional component of the Android decision-support workflow. The predicted fertility grade acts as the main link between sensor-derived soil data and advisory generation. Once the fertility grade is generated, the output is transferred to the advisory layer. This layer interprets the predicted fertility condition along with the individual soil parameters. The advisory layer does not stop at showing only the final fertility grade. It further converts the soil condition into parameter-wise guidance for NPK, pH, electrical conductivity, and moisture. This is important because different soil conditions require different advisory directions. For example, a low fertility case requires corrective guidance, a medium fertility case requires balanced-input and monitoring guidance, and a high fertility case requires maintenance-oriented guidance. The advisory layer is also connected with the recommendation modules of the Android prototype. These modules provide crop recommendation, fertilizer recommendation, fertilizer quantity calculation, water-quality advisory, and access to government resources. In this way, the system moves from soil measurement to fertility interpretation and then to practical decision support. The fertilizer quantity calculator further extends the usefulness of the system by allowing the user to estimate fertilizer requirements based on farm-size input. The water-quality advisory and government-resource section provide additional field-level support beyond fertility grading alone. The complete framework therefore follows a stepwise flow: sensor-derived soil input, fertility-grade prediction, parameter-wise interpretation, advisory generation, recommendation support, and Android-based display. This workflow is shown in Fig. 1. The proposed framework is not intended to claim full commercial deployment. It is presented as a research prototype that demonstrates how sensor-driven soil information can be converted into a mobile advisory and recommendation system suitable for farmer-oriented decision support.

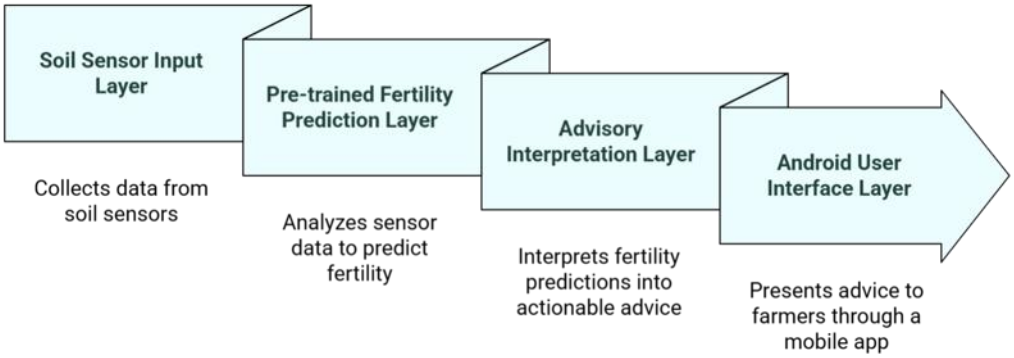


Fig. 1 Proposed mobile decision-support framework for soil fertility advisory

Table 1 presents the main layers of the mobile decision support system, providing a clear understanding of our proposed framework. The structure in the table highlights the workflow from sensor soil input into fertility level prediction into the explanation of the advisory, then to the recommendation and then the display via Android and finally validation. This breakdown also serves to explain that our prototype is not only a mobile application but also a connected decision-support workflow for soil-fertility advisories.

Table 1 Layers of the Proposed Mobile Decision-Support Framework

Framework Layer	**Function**	**Output**
Sensor Input Layer	Receives soil and contextual parameters	N, P, K, pH, EC, moisture, region, and fertilizer status
Fertility Prediction Layer	Classifies soil condition using a pre-trained ensemble-based model	Low, Medium, or High fertility grade
Advisory Interpretation Layer	Interprets fertility grade and parameter condition	NPK, pH, EC, and moisture advisory
Recommendation Layer	Converts interpretation into practical guidance	Crop, fertilizer, water-quality, and quantity recommendation
Android Interface Layer	Displays output through mobile screens	Farmer-facing advisory and recommendation workflow
Validation Layer	Checks system consistency and advisory behavior	Model-to-app match, scenario validation, and screenshot evidence

Each of the layers in the structure given Table 1 had a different responsibility that works together in an attempt to translate basic soil information from the field into intelligible recommendations for the farmer. The first layer is responsible for collecting raw soil and background information through the sensors, then the second layer calculates the level of fertility of the soil, the third and fourth layers are both responsible for adapting and tailoring the recommendation, and the fifth and final layer serves to visually present the output to the end user on their mobile phone.

5. Android Prototype Architecture

The Android prototype was developed to show sensor-based soil information in an understandable and usable way through a mobile application. The aim was to arrange the whole soil advisory process in a simple sequence and not only to show numerical soil values on a screen. Hence, the application in the same workflow combines soil data display, fertility-status output, parameter-wise advisory, crop and fertilizer recommendation, fertilizer calculation, water-quality guidance, and agricultural resource access. The application is based on different modules, each of which performs one part of the user journey. The user first enters the system through the Home/Dashboard screen and then goes on to select the state, city, and village. This step of location linking is useful as soil information makes more sense when linked to a specific village-level record or region. Once the location is chosen, the application displays the corresponding soil data. The Soil Data screen displays the main soil and contextual parameters used in the system. The variables are N_ppm, P_ppm, K_ppm, pH, EC_dSm, Moisture_VWC_%, Region, and Fertilizer Status. These values are presented before the advisory output to help the user understand the soil condition on which the later recommendation is based. Together with these parameters, the app also shows the fertility grade, which is produced by the pre-trained fertility prediction layer. The grade is presented as low, medium, or high and is the central output for the rest of the advisory process. The advisory section gives a more detailed interpretation of the soil condition once the fertility grade is available. The NPK advisory explains the status of the soil in terms of nutrients. The pH advisory will help you determine if the soil is acidic, neutral, or alkaline. The EC advisory gives guidance around salinity. The moisture advisory helps with interpretation of irrigation or water management. The distinct advisory components are important, as a single fertility label may not be a sufficient explanation for field-level decision-making. The app recommendation section extends the fertility output into more practical guidance. The crop recommendation module supports the crop suitability with respect to the interpreted soil condition. The fertilizer recommendation module provides fertilizer recommendations based on the fertility grade and soil parameter status. The fertilizer quantity calculator helps the user to enter farm-size details and get an estimated fertilizer requirement. This makes the app more useful at the planning level, as the recommendation is tied to a rough field requirement. The prototype also provides water-quality advisory and government-resource access. The water-quality advisory adds to facts on soil fertility and provides backup for water decisions. In the section with links of the government, you will find agricultural schemes or useful official links. These additions mean that the application is more than just a prediction display. Users can navigate from soil condition to advisory support to further agricultural resources. The Android workflow is shown in Fig. 2. It starts from the home/dashboard screen to location selection and soil data display, then to fertility-grade output, advisory modules, recommendation modules, fertilizer calculation, water-quality support, and government-resource access.

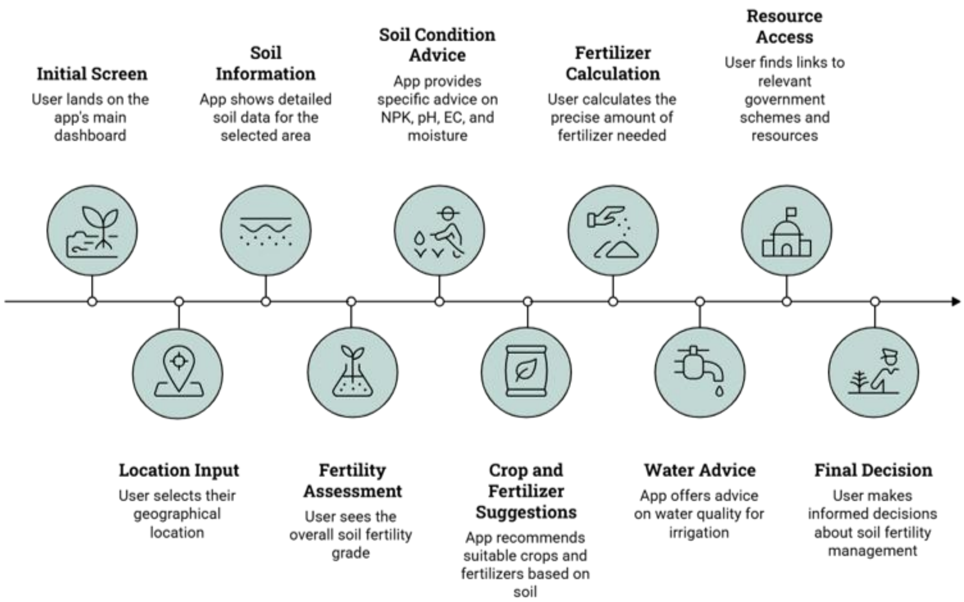


Fig. 2 Android prototype workflow for soil fertility advisory and recommendation

Table 2 summarizes the major modules of the Android prototype and their user-facing outputs. This table shows how each screen contributes to the complete mobile decision-support workflow.

Table 2 Android App Modules and Functions

Module	Purpose	User-Facing Output
Home/Dashboard	Provides the main entry point to the application	Access to soil fertility advisory workflow
State/City/Village Selection	Allows location-based selection of soil record	Selected state, city, and village
Soil Data Display	Shows sensor-derived soil parameters	N, P, K, pH, EC, moisture, region, and fertilizer status
Fertility Grade Display	Presents the predicted soil fertility status	Low, Medium, or High fertility grade
NPK Advisory	Interprets nutrient-related soil condition	Nutrient advisory for nitrogen, phosphorus, and potassium
pH Advisory	Interprets soil acidity or alkalinity	pH correction or maintenance guidance
EC Advisory	Interprets electrical conductivity condition	Salinity-related caution or normal-status guidance
Moisture Advisory	Interprets soil moisture condition	Moisture management or irrigation-related guidance
Crop Recommendation	Suggests crop suitability support	Crop recommendation based on soil condition
Fertilizer Recommendation	Provides fertilizer-related support	Suitable fertilizer guidance
Fertilizer Quantity Calculator	Estimates fertilizer requirement based on farm size	Fertilizer quantity estimate for field planning
Water-Quality Advisory	Provides water-related field support	Water-quality guidance
Government Scheme/Links	Gives access to agricultural resources	Government schemes and official resource links

As shown in Table 2, the prototype is developed as a connected workflow for mobile decision support. Each module has a specific role in converting the information from the soil sensors into an understandable advisory and recommendation output. This structure also allows for prototype validation, as each screen can be checked for working through screenshots, model-to-app output matching, and low, medium, and high fertility advisory scenarios.

6. Input-to-Advisory Traceability

One should highlight in a soil fertility advisory app the linkage between the prediction derived and the original soil inputs. A prediction can be a simple prediction page that does not show how the inputs were derived. The suggested system thus ensures input-to-advisory traceability by showing how each parameter in the soil record affects a specific section of the advisory. In the prototype application, the input soil values used are N ppm, P ppm, K ppm, pH, EC/dSm, moisture VWC%, region, and fertilizer status. They are first shown to the user in the soil data screen. In the fertility prediction and advisory interpretation screens, the same set of input parameter values is processed so that a clean connection between the soil record, its predicted soil fertility grade, and the advisory inputs appears on the Android app. Interpreting primarily depends on the levels of nutrients, nitrogen, potassium, and phosphorus in the soil. They influence the NPK and the fertilization modules, respectively. Where such parameters are deficient or show some sort of discrepancy, advisory output moves towards the corrective ones, while where the condition is satisfactory, advice focuses on maintenance. The state of acidity or alkalinity of a soil is explained with the help of the pH variable. This allows us to know about its properties, i.e., the behavior of a soil, such as the acidic one or the alkaline one. That is the interpretation part, and based on the given condition, the advisories provide respective corrections or corrective advice. Electricity conductivity, which can indicate any salinity problem with soil, i.e., the conductivity value EC/dSm, is also useful for managing the behavior. Electrical conductivity of EC/dSm: Where it causes some problem, warning guidance should be shown; or, where EC/dSm is ok, then the advisory advice about the general care for the quality of inputs is given. The same applies to any issues with water and irrigation that use the moisture parameter VWC%. The soil water status helps provide both moisture-related and water-quality-related information, as well as an extended advisory. Some of the inputs, namely 'Region' and 'Fertilizer Status,' are used merely as contextual inputs to help identify the particular soil record with a location on a map, as opposed to identifying a previously fertilized soil. Before fertilization, the fertilizer status inputs will provide this information. The following table lists how input parameters in the prototype's advisory output contribute to providing either some form of interpretation of fertility or advice and recommendation support.

Table 3. Input-to-Advisory Traceability

Input Parameter	Interpretation Role	Advisory or Recommendation Output
N_ppm	Indicates nitrogen condition in soil	Nitrogen advisory and fertilizer support
P_ppm	Indicates phosphorus condition in soil.	Phosphorus advisory and crop nutrition guidance
K_ppm	Indicates potassium condition in soil.	Potassium advisory and fertilizer recommendation
pH	Shows acidic, neutral, or alkaline soil behavior	pH correction or maintenance guidance
EC_dSm	Indicates electrical conductivity and salinity tendency.	EC-related caution or normal-status advisory
Moisture_VWC_%	Shows soil moisture condition	Moisture management and irrigation-related guidance
Region	Connects soil data with location context	Location-based soil record access
Fertilizer Status	Shows before/after fertilizer condition	Fertilizer-status-based interpretation

As shown in Table 3, all input parameters are linked with some explanation/advice given by the software to the user. In other words, if one can go, in our case, from input values through fertility status down to specific advice, that is the result of an overall design, and it is something very useful in defining the traceability of the advisory to the input value, while, on the contrary, it makes for us a powerful instrument for the validation of the prototype software in the advisory part against soil input values. The inputs to advisory are described in 3 as a general flow from each parameter to the advisory interpretation and prediction stages.

Figure 3 shows that each given parameter will have a particular influence on the prediction of advisories, which will then be transferred to the Android app as a recommendation result.

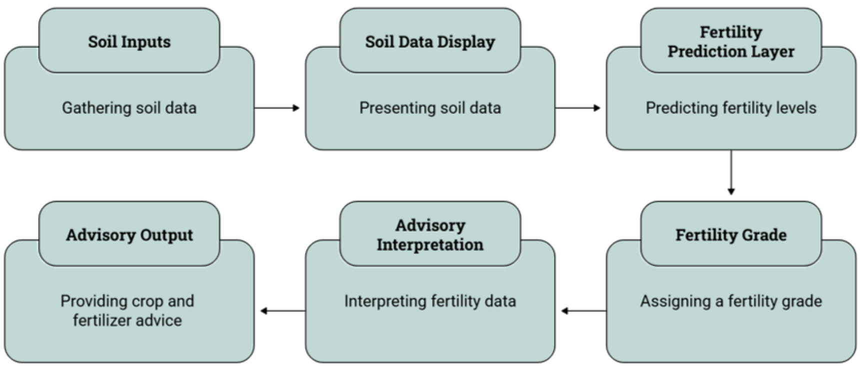


Fig. 3 Input-to-advisory traceability in the Android prototype for soil fertility.

7. Advisory Logic and Prototype Design

The prototype's advisory logic converts soil measurements into user-friendly guidance. Soil parameters such as N, P, K, pH, EC, and moisture are useful from a technical point of view, but the values alone may not be meaningful for field-level users. For this reason, the application does not stop at displaying soil values. It uses these values to show fertility status, explain the condition of important parameters, and provide recommendation support. Advising primarily makes use of three fertility class levels: Low, Medium, and High. The benefit of better communication with users is that the user gets to see the soil condition on a broader level, as opposed to solely seeing individual numerical results. With a low fertility class, the corrective suggestions of the application suggest, in terms of nutrient upgrading, fertilizer help, and soil monitoring enhancement. The more moderate the fertility class, the better the advisory recommendations will be. In this case, the soil is not treated as critical, but the user is guided to continue monitoring and use inputs carefully. When the soil is classified as high, the advisory message focuses on maintenance and controlled input use rather than urgent correction. The fertility-grade interpretation used in the prototype is shown in Table 4. This mapping helps explain how the app changes its advisory direction according to the predicted soil condition.

Table 4 Fertility classes and their advisory interpretation in the proposed prototype

Fertility Class	Interpretation in Prototype	Advisory Direction
Low	Soil condition requires corrective attention.	Nutrient improvement and closer field management guidance
Medium	Soil condition is moderate and should be monitored.	Balanced-input and monitoring guidance
High	Soil condition is comparatively well maintained.	Maintenance-oriented guidance

Along with the fertility class, the prototype also supports parameter-wise interpretation. The observed soil parameters are compared with suitable or recommended ranges wherever applicable so that the user can understand which values may require attention. For example, low nutrient values can be linked with the need for fertilizer support, while abnormal pH may indicate an acidic or alkaline imbalance. Similarly, EC is used for salinity-related interpretation, and moisture is used for water or irrigation-related guidance. This makes the advisory output more useful than a system that only displays a final fertility label. The recommendation screen extends this advisory logic into practical support. It includes fertility status display, soil parameter comparison, recommendation messages, fertilizer suggestions, and a fertilizer quantity calculator. Recommendations of fertilizers The fertilizer recommendation module makes use of the misinterpreted soil condition to present useful fertilizer recommendations, including appropriate fertilizer naming and image presentation (where applicable) in order to improve user understandability. The quantity calculator allows the user to enter farm-size details and obtain an estimated fertilizer quantity. This feature is important because it connects the advisory output with a field-use situation. The prototype also includes crop recommendation, water-quality advisory, and government resource access. The crop recommendation module supports crop suitability guidance based on the soil condition. The water-quality advisory provides additional support related to water use, while the government links section gives access to useful agricultural resources. These modules make the application broader than a basic prediction screen because the user can move from soil status to advisory interpretation, recommendation support, fertilizer planning, and external resource access. The major advisory components included in the recommendation workflow are summarized in Table 5.

Table 5. Advisory Components and Their Practical Role in User Support

Advisory Component	Purpose	User Benefit
Fertility Status Display	Shows Low, Medium, or High soil condition	Provides quick understanding of soil status
Soil Parameter Comparison	Compares observed values with suitable or recommended ranges	Helps identify which parameters need attention
Recommendation Message	Provides guidance based on fertility condition	Converts technical output into practical advice
NPK Advisory	Explains nutrient-related soil condition	Supports nutrient management and fertilizer planning
pH Advisory	Interprets acidic, neutral, or alkaline condition	Supports pH correction or maintenance guidance
EC Advisory	Interprets electrical conductivity condition	Provides salinity-related caution or normal-status

		guidance
Moisture Advisory	Interprets soil moisture condition	Supports water and irrigation-related understanding
Crop Recommendation	Suggests suitable crop options	Helps in crop selection support
Fertilizer Suggestion	Displays suitable fertilizer guidance	Supports practical nutrient planning
Quantity Calculator	Estimates fertilizer quantity from farm size	Assists field-level fertilizer planning
Water-Quality Advisory	Provides water-related guidance	Adds support for water-use decisions
Government Resource Links	Provides access to agricultural schemes or resources	Extends support beyond the app output

8. Validation Methodology

The purpose of the validation methodology was for testing if the Android prototype can function as a real-world soil fertility advisory system. Just to clarify, since the current study pertains to a prototype-level mobile decision-support system development (the validation presented in this study is no claims of commercial-scale deployment or large farmer level field-test). In practice the validation only checks the appropriate display of backend fertility output in the Android app, whether different fertility cases reach proper advisory direction and whether a general workflow is understandable and usable at prototype level. It was divided into three sections: model app output validation, Low/Medium/High advisory scenario validation, and prototype feasibility & usability. These validation checks show that the application is not purely a screen but an advisory workflow that connects soil data into fertility interpretation, recommendation support, and fertilizer planning as well as user-facing guidance.

8.1 Model-to-App Output Validation

Validation of the output from models to apps was performed using this architecture. Confidence Level: Info (75%) Model-to-Apps Output Validation Confirming the Correctness of Fertility Grade in Android Application This step ensured the correct rendering of the fertility grade generated by the backend prediction layer in the Android application. This is important because when showing advisory messages and recommendation modules, it depends on the fertility grade shown to the user. If the Android display does not align with the backend prediction, it can lead to misleading advisory outputs.

For this validation, the selected soil records were pushed through the pre-trained fertility prediction layer. The backend output was then looked at and matched with the fertility grade shown inside the Android application. A few representative cases from the Low, Medium and High fertility categories were reviewed, just to ensure that all three classes were visible properly in the app. This validation was not meant to measure the model accuracy again or anything like that. The model evaluation is part of a different model development stage. Here in this paper, the main focus is basically to confirm that the prediction output is wired up correctly to the Android interface.

Table 6 Model-to-App Output Validation

Test Case	Backend Prediction	Android Display	Match Status
Low fertility case	Low	Low	Matched
Medium fertility case	Medium	Medium	Matched
High fertility case	High	High	Matched

As shown in Table 6, the Android application displayed the same fertility grade as the backend prediction layer for the selected test cases. This confirms that the app output is consistent with the prediction result and that the advisory workflow is based on the correct fertility category.

8.2 Low/Medium/High Advisory Scenario Validation

In the second stage of validation, we examined whether the app was providing suitable advisory guidance for various fertility situations. Because Low, Medium, and High fertility classes need different kinds of guidance, we tested the prototype with representative cases coming from each one.

With a Low fertility case, what we expected was corrective direction. So, the app should basically steer the user toward nutrient upgrades, fertilizer support, and more frequent checking. For a Medium fertility scenario, the expected output became balanced advisory, in other words the soil condition is considered moderate and then the user gets nudged toward steady monitoring plus careful input handling, and for the high fertility case, the advisory direction was intended to lean toward maintenance and controlled fertilizer use instead of making unnecessary corrections, as we observed in the review.

Table 7. Low/Medium/High Advisory Scenario Validation

Fertility Case	Expected Advisory Type	App Advisory Direction	Validation Result
Low	Corrective advisory	Nutrient improvement, fertilizer support, and closer monitoring	Validated
Medium	Balanced advisory	Balanced input use, regular monitoring, and suitable crop/fertilizer guidance	Validated
High	Maintenance advisory	Maintenance guidance, controlled fertilizer use, and avoidance of unnecessary input	Validated

As shown in Table 7, the advisory direction changes according to the fertility class. This supports the practical value of the prototype because the application does not show the same recommendation pattern for all soil conditions. Instead, it provides guidance based on the predicted fertility status and related soil parameter interpretation.

8.3 Prototype Feasibility and Usability Assessment

The third validation step was about if the Android workflow feels understandable, usable, and kind of fitting for prototype-level soil advice delivery. It looked at things like how clear the screens are, the order the user sees them, whether the soil information is easy to read, and if the recommendation modules actually help in a meaningful way.

So basically, the workflow was checked from the user's perspective. The user starts with choosing a location, then looks at the soil data, checks the fertility grade, and reads the advisory messages, and after that goes over to crop recommendation, then fertilizer recommendation, then the fertilizer quantity calculation, followed by water quality advisory, and finally government resource access. That sequence mattered because it lets the user sort of move slowly from the soil record selection toward practical decision support without jumping too fast into the recommendations.

The feasibility and usability assessment is summarized in Table 8.

Table 8. Prototype Feasibility and Usability Assessment

Assessment Point	Evidence in Prototype	Assessment Result
Workflow completeness	User can move from location selection to advisory and recommendation output	Feasible at prototype level
Soil data readability	N, P, K, pH, EC, moisture, region, and fertilizer status are displayed clearly	Feasible
Fertility-status clarity	Low, Medium, or High grade is shown in the app	Feasible
Advisory understanding	NPK, pH, EC, and moisture advisories are shown in user-facing form	Feasible
Recommendation support	Crop, fertilizer, and water-quality modules are included	Feasible
Fertilizer planning	Calculator estimates fertilizer quantity from farm-size input	Feasible
Resource support	Government-resource links are included	Feasible
Deployment limitation	Full-scale live farmer deployment was not conducted	Future work required

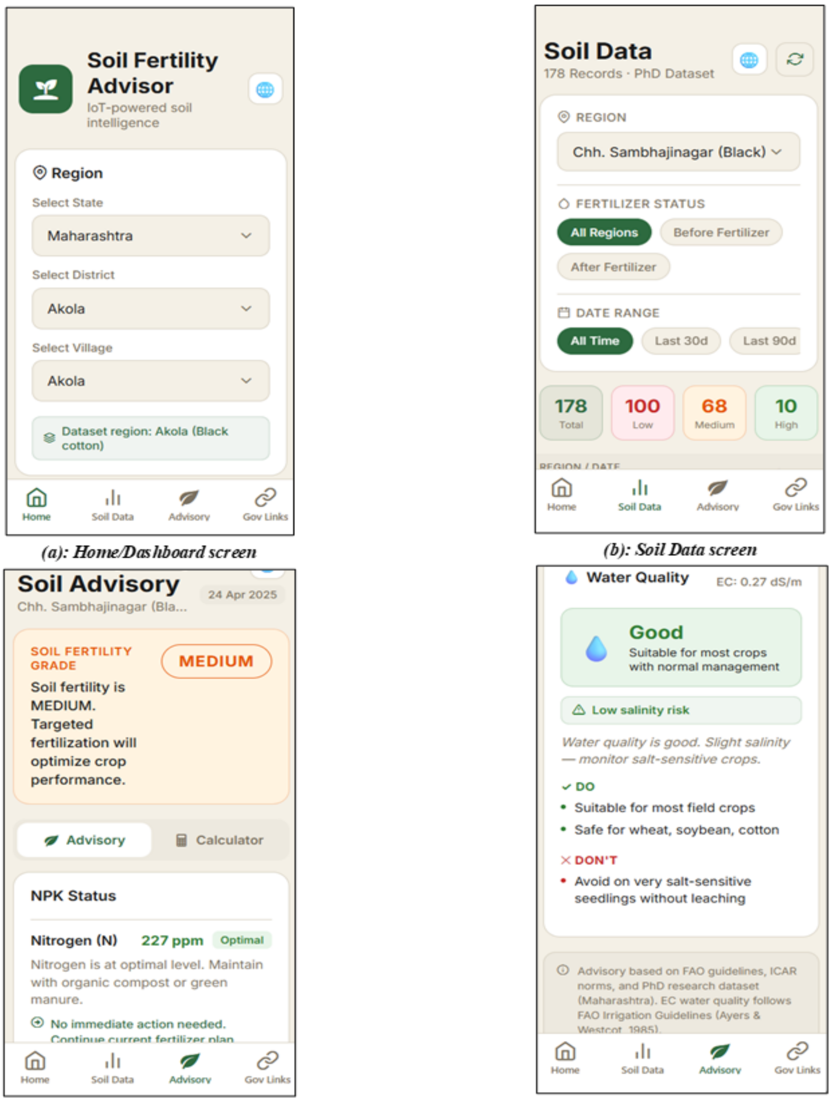
As shown in Table 8, the Android prototype is feasible at the prototype level because it provides a complete and understandable advisory workflow. The application allows soil data to be viewed, interpreted, and converted into advisory and recommendation output. However, the study remains limited to prototype-level validation. Future work may include real-time sensor streaming, multilingual support, larger farmer testing, and region-specific refinement of advisory rules.

9. Results and Discussion

The results and discussion section presents the functional outcome of the developed Android-based soil fertility advisory prototype. Here the focus is not really on re-evaluating the prediction model, more on looking at how the backend fertility output gets translated into a user facing mobile workflow. In other words, it discusses how the implemented screens connect, how advisory modules were organized, what validation findings showed, how useful it feels in practice, and also what the limitations are for this prototype when it is used as a soil fertility decision support system.

9.1 Android Prototype Screens and Workflow

The developed Android prototype shows that soil-fertility assessment can be provided via a structured mobile decision-support flow. The application does not only show raw soil readings; it also arranges soil data, fertility status, advisory notes, recommendation modules, fertilizer planning assistance, and water quality guidance, plus access to government resources all inside one connected interface. Fig. 4 displays representative screens from the developed prototype, providing a quick walkthrough of the process.



(a): Home/Dashboard screen *(b): Soil Data screen*

(c): Soil Advisory screen *(d): Water-quality advisory screen*

Fig. 4. *Representative screens of the developed Android-based soil fertility advisory prototype: (a) Home/Dashboard screen, (b) Soil Data screen, (c) Soil Advisory screen, and (d) Water-quality advisory screen.*

The workflow starts at the Home/Dashboard screen, where the user can reach location-based soil information through state, city, and village selection. Once the location is chosen, the Soil Data screen then presents important soil parameters including N, P, K, pH, EC, moisture, region, and fertilizer status in a clear format. Next, the predicted fertility grade appears as Low, Medium, or High, and then advisory and recommendation results follow right after. Overall, this screen sequence suggests the prototype gives a full movement, from choosing a soil record up to receiving practical advice on the device. Rather than leaving the prediction strictly as a backend thing, the system translates the output into a mobile view that users can actually understand. So the screenshots are included as implementation proof that the Android modules work, and not as a standalone validation process.

9.2 Functional Outcomes of the Prototype

The main goal of this prototype is to integrate soil data, fertility forecasting, advisory insights, and recommendation support into one user-friendly Android interface. Unlike separate components, it keeps everything interconnected. Users can easily check soil parameters through the Soil Data module, which simplifies fertility predictions into clear categories, making complex soil numbers more accessible. The advisory module then steps in, offering detailed guidance on NPK, pH, EC, and moisture levels. This is vital because a single fertility label often isn't enough for daily decisions. By combining advisory details with the fertility classification, the prototype provides a clearer picture of soil health and actionable steps.

The recommendation modules take the system a step further. Crop and fertilizer recommendation screens are tailored to the predicted fertility status and current soil conditions, giving users decision-making support. The fertilizer calculator also plays a role, estimating needed amounts based on farm size. Additionally, the water-quality advisory module adds context about field conditions. In essence, this prototype functions as a comprehensive advisory system, not just a predictive tool.

9.3 Interpretation of Validation Findings

The validation findings in tables 6, 7, and 8 clearly demonstrate the Android prototype’s consistent performance. Table 6 specifically shows that the fertility grades displayed in the app aligned perfectly with the backend predictions across Low, Medium, and High fertility cases. This connection between the prediction layer and the mobile interface works seamlessly. Moving to Table 7, it reveals how the advisory direction varied based on fertility categories. For Low fertility, the advice was corrective; for Medium, it was balanced and focused on monitoring and input guidance; and for High fertility, the advice was more maintenance-oriented. This distinction underscores the need for tailored management strategies depending on the fertility level. Table 8 provides further evidence of the prototype’s feasibility and usability. It outlines a comprehensive workflow that starts with selecting locations, viewing soil data, interpreting fertility status, generating advisories, supporting recommendations, planning fertilizers, advising on water quality, and accessing government resources. This detailed functionality supports the practical application of the prototype as a mobile soil-fertility advisory system.

9.4 Practical Implications and Limitations

The results show that the proposed Android prototype seamlessly connects soil sensing, fertility prediction, and user-facing decision support. Unlike many smart-agriculture studies that address these components separately, this work integrates them into a single mobile workflow, significantly enhancing the system’s utility. Integrating these elements makes soil-fertility prediction more meaningful when presented clearly. Backend models can classify soil fertility, but their impact grows when delivered through a user-friendly interface that supports recommendations and planning. The prototype includes fertility grades, parameter-wise advisories, crop and fertilizer recommendations, a fertilizer calculator, water-quality advisories, and access to government resources. Yet, the current study primarily focuses on validating the prototype rather than full commercial deployment or widespread farmer adoption. Future work could involve real-time sensor streaming, multilingual support, broader farmer feedback, and refining region-specific advisories. In essence, the results illustrate that soil-fertility prediction can be effectively transformed into a compact Android-based advisory workflow for practical decision support.

10. Conclusion

This paper introduced an Android-based soil fertility decision-support system designed to offer sensor-driven advice directly to farmers. Motivated by the gap between soil data analysis and user-friendly decision support in smart-agriculture systems, the prototype incorporated several key features: location-based soil data access, real-time display of soil parameters, fertility status interpretation, parameter-specific advisories, crop and fertilizer recommendations, estimated fertilizer quantities, water quality guidance, and easy access to government resources all packaged in a user-friendly mobile application. Tests confirmed that the backend fertility outputs appeared consistently in the Android interface, and the prototype offered suitable advisory directions for Low, Medium, and High fertility scenarios. Academic reviews suggested that the workflow was both clear and functional at this prototype stage. This research thus demonstrates that soil fertility predictions can be effectively transformed into a practical, mobile-advisory format rather than remaining confined to mere backend models or raw sensor data displays. However, the current study focuses solely on validating the prototype's functionality and does not ensure full-scale field deployment or commercial readiness. Future improvements could include real-time sensor streaming, wider farmer validations, multilingual support, cloud-based backend connectivity, and tailored regional advisory services. Overall, the proposed prototype represents a crucial step toward mobile soil fertility decision support, especially relevant for smart agriculture initiatives in India and the Maharashtra region.

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The authors have no competing interests to declare that are relevant to the content of this article.

Author contributions

Farhat Shaikh contributed to the conceptualization of the study, data collection, prototype design, methodology development, implementation, analysis, manuscript drafting and revision.

Satish Sankaye provided research supervision, technical guidance, methodological review and manuscript refinement. Both authors reviewed and approved the final version of the manuscript.

Ethics approval

This study did not involve human participants, animal subjects or clinical data. The work was based on soil sensor measurements and prototype-level system validation.

Consent to participate

Not applicable.

Consent to publish

Not applicable.

Data availability

The data used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Code availability

The prototype code is available from the corresponding author on reasonable request.

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