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# Agrotech: Design And Implementation Of An Ai-Driven Virtual Soil Testing And Smart Agriculture Support System

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***Abstract*** **- Soil health assessment is an essential requirement for improving crop productivity and sustainable agricultural planning. Traditional soil testing methods are accurate but slow, require laboratory facilities, and are often inaccessible to farmers living in remote regions, particularly in mountainous states like Uttarakhand. Recent advancements in artificial intelligence (AI) and image processing have enabled rapid soil-type prediction using smartphone images. This research paper critically examines the emerging research trends in soil image classification, color–texture analysis, CNN-based deep-learning models, and the role of lightweight architectures such as MobileNetV2, Yolo and Binary Classification Models. It evaluates existing methodologies, highlights the benefits of digital soil analysis, and discusses how datasets improve prediction accuracy. The paper concludes that image-based soil analysis combined with machine learning can significantly support farmers by providing real-time soil diagnostics, crop recommendations, and nutrient insights through mobile applications, leading to more sustainable and data-driven agriculture and access the Government Schemes.**

**In addition to soil diagnostics, the integration of a digital marketplace platform is proposed to empower rural farmers economically. Such a platform can enable farmers to directly list and sell their agricultural products—such as crops, organic produce, and soil-specific harvests—to consumers, retailers, or wholesalers, reducing dependency on middlemen. By linking soil health insights with marketplace recommendations, farmers can be guided on what crops to grow based on soil conditions and current market demand. This integration enhances transparency, ensures better pricing, and promotes sustainable agricultural practices by aligning production with demand.**

## 1. INTRODUCTION

The initial thought process for this project was quite straightforward: if a farmer can take a picture of the soil using a phone, can we give them useful advisory output from within the same app?
However, as we progressed, we understood that we cannot just provide one advisory screen. A practical user will require an end-to-end process that includes secure login, advisory for taking pictures, valid validation, understandable report, crop selection, fertilizer recommendations, Government Schemes, Marketplace and support details.
Therefore, we developed our system as an end-to-end process, rather than a showcase of a single ML model. The final system integrates AI inference and service components all in one place, so the user does not have to navigate between multiple apps.

## 2. LITERATURE REVIEW

The application of Artificial Intelligence (AI) and Machine Learning (ML) in agriculture has significantly increased in recent years, particularly in soil analysis and crop recommendation systems. Lightweight deep learning architectures such as MobileNet, proposed by Howard et al., have enabled efficient image-based classification on mobile devices, making them suitable for rural applications with limited computational resources [1]. In addition, advanced architectures such as He et al. [2] and Tan and Le [3] have further improved image classification accuracy and scalability in agricultural applications.

Several studies have focused on soil classification using image processing techniques. Sharma and Bisht demonstrated that Convolutional Neural Networks (CNNs) can effectively classify soil texture based on visual features such as color and texture [4]. Similarly, Patel, V. et al. explored image-based nutrient estimation approaches, although they highlighted that predicting chemical properties purely from images remains a challenging task [5].

Machine learning has been widely used in precision agriculture for crop recommendation. Singh, R. et al. discussed the role of ML in improving agricultural productivity through data-driven decision-making [6]. Rajak, R.K. et al. developed a crop recommendation system using soil parameters such as N, P, and K, showing improved yield prediction [7]. A notable contribution is the AgroSense system [8], which integrates deep

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learning-based soil image analysis with nutrient profiling and crop recommendation, forming a foundation for intelligent agricultural advisory systems. Other approaches such as K-Nearest Neighbors (KNN), explored by Zhang and Kumar [9], and Artificial Neural Networks (ANN), proposed by Madhuri and Indiramma [10], have also shown promising results in crop recommendation tasks.

Recent research has explored deep learning-based approaches for improved accuracy. Motwani, A., Patil, P., Nagaria, V., Verma, S., and Ghane, S. proposed a soil analysis system using ML techniques [11], while Manjula, E. and Djodiltachoumy, S. developed a deep learning model for crop recommendation based on soil nutrients [12]. Ensemble and hybrid approaches, such as those proposed by Kulkarni et al. [13] and Nguyen, H. and Lopez, C. [14], combine multiple algorithms to enhance prediction performance and robustness.

The integration of IoT and machine learning has enabled real-time monitoring systems. Sunandini, M., Sree, K.H., Deepiga, R., and Gokulapriya, A. developed a smart soil monitoring system using IoT sensors and ML algorithms [15], which allows continuous tracking of soil parameters. However, such systems require additional hardware, which may limit accessibility for small-scale farmers.

Recent advancements focus on multimodal learning approaches. Shamsuddin, D., Danilevicz, M.F., Al-Mamun, H.A., Bennamoun, M., and Edwards, D. demonstrated that combining image, weather, and temporal data significantly improves prediction accuracy [16]. Similarly, Liu, P., Zhang, X., Li, M., and Guo, H. proposed integrating remote sensing data with deep learning models for better crop yield prediction [17]. Ensemble learning models such as RicEns-Net proposed by Yewle, A.D., Mirzayeva, L., and Karakuş, O. further improve prediction performance by combining multiple data sources [18]. Additionally, remote sensing-based crop mapping using satellite imagery, as explored by Zhao et al. [19], has enhanced large-scale agricultural monitoring.

Explainable AI (XAI) is gaining importance in agricultural systems. Turgut, O., Kok, I., and Ozdemir, S. introduced AgroXAI, which improves transparency and interpretability in crop recommendation systems, thereby increasing user trust [20].

Comprehensive reviews by Garcia, E. and Sharma, P. [21] and Lakshmi, P. and Rajeev, S. [22] highlight the rapid growth of AI and IoT applications in agriculture, while also identifying challenges such as data scarcity, scalability, and model interpretability. Li, J., Chen, D., and Morris, D. emphasized the issue of limited labelled datasets in agricultural applications, which directly impacts model performance [23]. Furthermore, Kouadio and Chevalier [24] demonstrated that soil fertility prediction models depend heavily on high-quality input data.

Recent developments in Edge-AI and cloud-based systems have enabled real-time decision-making in agriculture. Peng, L., Zhou, W., and Gao, L. proposed a hybrid Edge-AI framework for crop recommendation [25], while Banerjee, S., Mukherjee, A., and Kamboj, S. introduced advanced concepts such as digital twins for precision agriculture [26]. Additionally, modern AI-driven frameworks integrating deep learning for agricultural optimization have been discussed by Dey and Sharma [27].

## 3. PROBLEM MOTIVATION

In practical agricultural scenarios, farmers often lack timely access to laboratory-based soil analysis reports or depend heavily on informal local guidance. This situation introduces significant uncertainty in crop selection, making the decision-making process largely speculative.

The proposed system aims to provide rapid, first-level advisory support within a short time frame using accessible technological solutions. It is important to emphasize that this system is designed to complement, rather than replace, conventional laboratory-based soil testing. Instead, it serves as an initial decision-support tool to assist farmers in making more informed and data-driven choices regarding crop selection.

## 4. SYSTEM WORKFLOW IMPLEMENTED

User registration begins with mobile number verification, where an OTP (One-Time Password) is sent to the user's mobile phone and verified successfully (Fig:1). After verification, the application requests location permission to enable location-based services and improve accuracy in soil-related recommendations. Once the setup process is completed, the Home tab displays a short instructional video that guides users on how to capture a clear and proper soil image for accurate analysis and better results.


**Fig. 1. User Authentication Process**

The user captures a soil image using the capture button and then clicks on the "Analyse Image" option to start the analysis process. If the uploaded image does not contain soil, the application displays a warning message to ensure accurate input. When a valid soil image is detected, the analysis pipeline is executed, and the report page is opened displaying the overall soil fertility score along with detailed nutrient values. Users can further scroll to access the crop recommendation section, where suitable crops based on soil conditions are suggested. Additionally, fertilizer recommendations are provided to guide


**Fig. 2. System Architecture**

nutrient improvement and enhance soil productivity. On further scrolling, users can explore government schemes and expert monitoring options for additional agricultural support. The home interface is designed to provide streamlined and intuitive access to the integrated marketplace platform, ensuring smooth and efficient user navigation throughout the application.

## 5. SYSTEM MODULES WE BUILT

From the implementation perspective, the system was divided into multiple functional modules to ensure scalability, maintainability, and efficient workflow management. These modules include authentication with OTP verification, location permission and user context handling, soil image guidance and capture, soil/non-soil validation, soil analysis and nutrient estimation logic, fertility score report generation, crop recommendation, fertilizer suggestion, government schemes, expert monitoring, and the integrated marketplace platform. Each module is designed to perform a specific responsibility within the application architecture, enabling smooth interaction between the frontend, backend, and AI-based analysis components. Additionally, a clear separation has been maintained between the government schemes section and the marketplace platform so that AI prediction pipelines, marketplace operations, and government scheme updates can be managed independently without affecting each other. This modular design improves system flexibility, simplifies future enhancements, and ensures efficient maintenance of the overall application.

## 6. DESIGN CHOICES AND LEARNING

Several important design decisions were taken during the development of the system to improve usability, prediction reliability, and long-term maintainability. One of the key decisions was to validate uploaded images at an early stage to identify non-soil images before running the prediction pipeline. This early validation significantly improved the accuracy and consistency of downstream soil analysis results. Another important decision was to display the fertility score and nutrient information before presenting crop recommendations, as users found numerical soil insights more meaningful and trustworthy prior to receiving agricultural suggestions. The marketplace module was also maintained separately from the government schemes section because government-related information changes frequently, and separating these modules improves system maintainability and simplifies updates. Additionally, the initial version of the application focused more on creating an actionable and user-friendly workflow rather than emphasizing the technical complexity of the AI model stack, ensuring that users could easily understand and benefit from the platform's recommendations and services.

## 7. CURRENT LIMITATIONS

Despite the effectiveness of the current system, several limitations still exist that need further improvement in future versions. The nutrient values generated by the system are advisory-level estimates and should not be considered as exact laboratory measurements. The accuracy and reliability of the analysis are also highly dependent on the quality of the captured soil image, meaning unclear or improperly captured images can affect prediction performance. Additionally, the system still requires broader district-level data coverage to improve generalization across different geographical regions and soil conditions. Another limitation is that the confidence and robustness of model predictions can be further enhanced by incorporating multimodal inputs such as environmental data, weather conditions, and sensor-based measurements alongside soil images.

## 8.MATHEMATICAL FORMULATION

### A. *8.1 Accuracy*

Classification accuracy is defined as:

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number Of Predictions}}$$

Using confusion matrix notation:

$$\text{Accuracy} = \frac{\sum_{i=1}^{n} C_{ii}}{\sum_{i=1}^{n}\sum_{j=1}^{n} C_{ij}}$$

**Where:**

- $C_{ii}$= correctly classified samples of class i.
- $C_{ij}$ = samples of actual class iii predicted as class j

### B. *8.2 Precision*

Precision measures how many predicted samples of a class are actually correct.

$$\text{Precision} = \frac{TP}{TP + FP}$$

**Where:**

- TP = True Positives
- FP = False Positives

### C. *8.3 Recall*

Recall measures how many actual samples of a class are correctly identified.

$$\text{Recall} = \frac{TP}{TP + FN}$$

**Where:**

- FN = False Negatives

### D. *8.4 F1-Score*

F1-score is the harmonic mean of precision and recall.

$$\text{F1} = 2\times \frac{Precision \times Recall}{Precision + Recall}$$

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### *E. 8.5 Fertility Score Computation*

**Method Overview:**
The proposed system estimates soil fertility using a rule-based point scoring mechanism. After predicting the soil type from the input image, the system retrieves the corresponding nutrient and soil-parameter values (district averages/estimates). Fertility is then quantified as a composite score computed from five key indicators: Nitrogen (N), Phosphorus (P), Potassium (K), soil pH, and Organic Matter (OM). Each indicator contributes a discrete number of points based on whether the value falls within an agronomically desirable band.

#### *1) Point-Based Fertility Score*

For each indicator x∈ {N, P, K, pH, OM} the system assigns:

- **20 points** if the value lies in the optimal range
- **15 points** if the value lies in the near-optimal range
- **10 points** otherwise (outside the target bands)

The fertility score F is computed as:

$$F = S_N(N) + S_P(P) + S_K(K) + S_{pH}(pH) + S_{OM}(OM)$$

$$S_x(\cdot) \in \{10,15,20\}, F \in [50,100]$$

#### *2) Threshold Bands Used for Point Assignment*

**(1) Nitrogen (N):**

- $S_N$=20 if 300 ≤ N ≤ 400
- $S_N$=15 if 250 ≤ N < 300 or 400 < N ≤ 450
- $S_N$=10 otherwise

**(2) Phosphorus (P):**

- $S_P$=20 if 25 ≤ P ≤ 50
- $S_P$=15 if 15 ≤ P < 25 or 50 <P ≤60
- $S_P$=10 otherwise

***(3) Potassium (K):***

- $S_K$ = 20 if 200 ≤ K ≤ 300
- $S_K$ = 15 if 150 ≤ K < 200 or 300 < K ≤ 350
- $S_K$ = 10 otherwise

***(4) Soil pH:***

- $S_{pH}$ = 20 if 6.0 ≤ pH ≤ 7.5
- $S_{pH}$ = 15 if 5.5 ≤ pH < 6.0 or 7.5 < pH ≤ 8.0
- $S_{pH}$ = 10 otherwise

***(5) Organic Matter (OM):***

- $S_{OM}$ = 20 if 1.5 ≤ OM ≤ 2.5
- $S_{OM}$ = 15 if 1.0 ≤ OM < 1.5 or 2.5 < OM ≤ 3.0
- $S_{OM}$ = 10 otherwise

**Fertility Level Mapping:**

The numeric fertility score is converted to a categorical fertility level (Low/Medium/High) for decision-making and crop recommendation. The system uses configurable thresholds; if district-specific thresholds are not available, default thresholds are applied:

$$\text{Fertility Level(F)} = \begin{Bmatrix} Low, & F \leq 59 \\ Medium, & 60 \leq F \leq 79 \\ High, & F \geq 80 \end{Bmatrix}$$

## 9. RESULT

The proposed AI-driven soil classification system was evaluated using standard performance metrics including accuracy, precision, recall, F1-score, and confusion matrix analysis. The experimental results demonstrate that the model is capable of effectively classifying different soil types using image-based inputs. The model achieved an overall **test accuracy of 85.14%**, indicating strong classification capability across multiple soil categories. Furthermore, the system achieved a **top-3 accuracy of 97.30%**, which shows that the correct soil class is highly likely to appear among the top predicted outputs. This is particularly useful in agricultural advisory systems where multiple recommendations can assist users in decision-making.

The classification report provides detailed insights into the performance of each soil category. **Alluvial soil** achieved a precision of **0.8831**, recall of **0.7234**, and F1-score of **0.7953** with a support value of 94 samples. The comparatively lower recall indicates that some Alluvial soil samples were misclassified as other soil types due to similarity in texture and color characteristics.

**Black soil** demonstrated excellent performance with a precision of **0.9167**, recall of **0.9429**, and F1-score of **0.9296** across 70 samples. The high recall value indicates that the majority of Black soil samples were correctly identified by the model. Similarly, **Red soil** achieved a precision of **0.9333**, recall of **0.7778**, and F1-score of **0.8485**, reflecting reliable prediction performance despite moderate confusion with visually similar soil classes.

The model also performed strongly on **Mountain soil**, achieving a recall of **0.9655** and an F1-score of **0.8750**. Out of 58 samples, 56 were correctly classified, indicating that the model successfully learned the distinct visual patterns associated with this soil category. **Laterite soil** achieved a precision of **0.7349**, recall of **0.8971**, and F1-score of **0.8079**, demonstrating stable classification performance.

For **Sandy soil**, the model achieved perfect classification performance with precision, recall, and F1-score values of **1.0000**. All 8 Sandy soil samples were correctly identified without any misclassification. However, since the support value for Sandy soil is relatively small, additional samples may further validate the consistency of this performance.

The confusion matrix analysis further explains the behaviour of the classification model. Most soil categories were accurately classified with minimal confusion.

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**Fig. 3. Classification Report and Confusion Matrix of the Proposed Soil Classification Model**

```
Test accuracy: 0.8514
Test top-3 accuracy: 0.9730

Classification report:
              precision    recall  f1-score   support

    Alluvial     0.8831    0.7234    0.7953        94
       Black     0.9167    0.9429    0.9296        70
         Red     0.9333    0.7778    0.8485        72
    Mountain     0.8000    0.9655    0.8750        58
    Laterite     0.7349    0.8971    0.8079        68
       Sandy     1.0000    1.0000    1.0000         8

    accuracy                         0.8514       370
   macro avg     0.8780    0.8844    0.8761       370
weighted avg     0.8615    0.8514    0.8503       370

Confusion matrix (rows=true, cols=pred):
[[68  2  0 14 10  0]
 [ 4 66  0  0  0  0]
 [ 2  2 56  0 12  0]
 [ 2  0  0 56  0  0]
 [ 1  2  4  0 61  0]
 [ 0  0  0  0  0  8]]
```

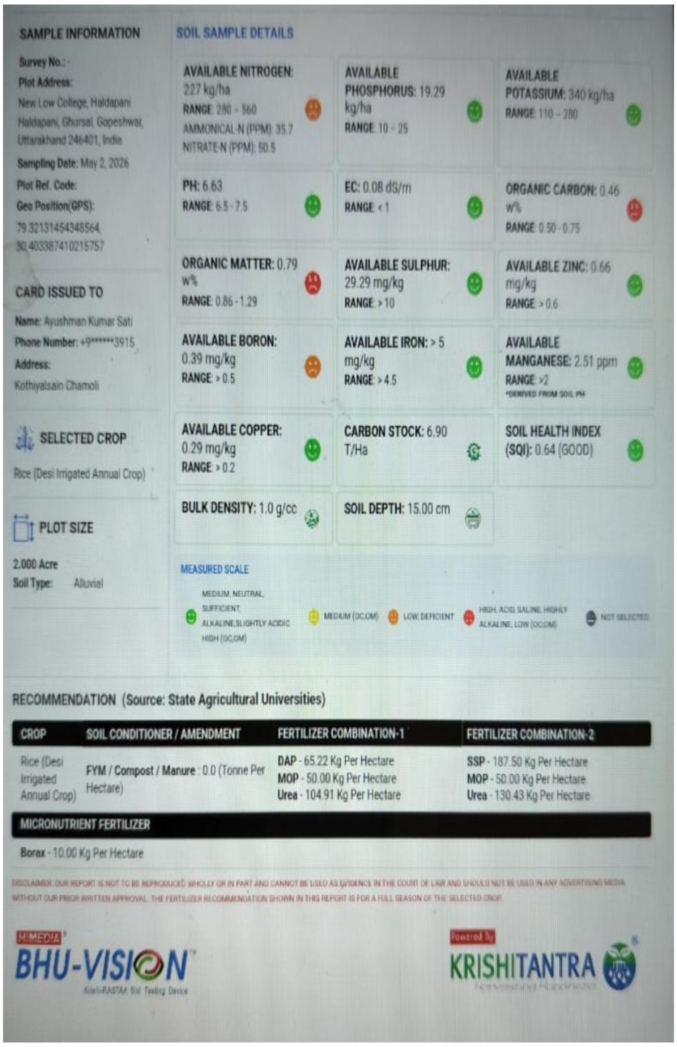
The classification results demonstrated that the model performed effectively across different soil categories with a high level of prediction accuracy. Most of the Alluvial soil samples were correctly classified, although a small number of samples were occasionally confused with visually similar soil types. Black soil achieved highly accurate predictions with very few misclassifications, indicating that the model was able to recognize its distinguishing features effectively. Red soil samples were also classified successfully, with only minor confusion occurring among soils with similar textures and color patterns. Mountain soil showed excellent classification performance, demonstrating that the model successfully learned its unique visual characteristics. Similarly, Laterite soil maintained stable and reliable prediction performance throughout the dataset. Sandy soil produced the best results, as all samples were classified correctly during testing without any observed misclassification. Overall, the results indicate that the model was capable of learning meaningful visual patterns for accurate soil type identification across multiple soil categories.

Some misclassifications occurred between Alluvial, Red, and Laterite soils, mainly because these soil types share similar visual characteristics such as texture, moisture appearance, and color distribution. Despite these challenges, the model maintained stable performance across all classes.

The macro average precision, recall, and F1-score were **0.8780**, **0.8844**, and **0.8761**, respectively, indicating balanced classification capability across different soil categories. Similarly, the weighted average F1-score of **0.8503** reflects strong overall model performance when considering class distribution.

Overall, the experimental results confirm that the proposed AI-based virtual soil testing system can effectively classify soil types with high reliability and balanced performance. The integration of image-based soil analysis with AI techniques demonstrates strong potential for real-time agricultural applications. Future improvements such as larger datasets, advanced augmentation techniques, and integration of sensor-based soil parameters may further enhance system accuracy and robustness.

**Fig. 4. Laboratory Soil Health Report Used for Validation**



SAMPLE INFORMATION

Survey No.: -
Plot Address: New Low College, Haldapani Haldapani, Ghursal, Gopeshwar, Uttarakhand 246401, India
Sampling Date: May 2, 2026
Plot Ref. Code:
Geo Position(GPS): 79.32131454348564, 30.403387410215757

CARD ISSUED TO

Name: Ayushman Kumar Sati
Phone Number: +9******3915
Address: Kothiyalsain Chamoli

SELECTED CROP

Rice (Desi Irrigated Annual Crop)

PLOT SIZE

2.000 Acre
Soil Type: Alluvial

SOIL SAMPLE DETAILS

AVAILABLE NITROGEN: 227 kg/ha
RANGE: 280 - 560
AMMONICAL-N (PPM): 35.7
NITRATE-N (PPM): 50.5

AVAILABLE PHOSPHORUS: 19.29 kg/ha
RANGE: 10 - 25

AVAILABLE POTASSIUM: 340 kg/ha
RANGE: 110 - 280

PH: 6.63
RANGE: 6.5 - 7.5

EC: 0.08 dS/m
RANGE: < 1

ORGANIC CARBON: 0.46 w%
RANGE: 0.50 - 0.75

ORGANIC MATTER: 0.79 w%
RANGE: 0.86 - 1.29

AVAILABLE SULPHUR: 29.29 mg/kg
RANGE: > 10

AVAILABLE ZINC: 0.66 mg/kg
RANGE: > 0.6

AVAILABLE BORON: 0.39 mg/kg
RANGE: > 0.5

AVAILABLE IRON: > 5 mg/kg
RANGE: > 4.5

AVAILABLE MANGANESE: 2.51 ppm
RANGE: >2
*DERIVED FROM SOIL PH

AVAILABLE COPPER: 0.29 mg/kg
RANGE: > 0.2

CARBON STOCK: 6.90 T/Ha

SOIL HEALTH INDEX (SQI): 0.64 (GOOD)

BULK DENSITY: 1.0 g/cc

SOIL DEPTH: 15.00 cm

MEASURED SCALE

MEDIUM, NEUTRAL, SUFFICIENT, ALKALINE, SLIGHTLY ACIDIC HIGH (OC,OM)
MEDIUM (OC,OM)
LOW, DEFICIENT
HIGH, ACID, SALINE, HIGHLY ALKALINE, LOW (OC,OM)
NOT SELECTED

RECOMMENDATION (Source: State Agricultural Universities)

| CROP | SOIL CONDITIONER / AMENDMENT | FERTILIZER COMBINATION-1 | FERTILIZER COMBINATION-2 |
|---|---|---|---|
| Rice (Desi Irrigated Annual Crop) | FYM / Compost / Manure : 0.0 (Tonne Per Hectare) | DAP - 65.22 Kg Per Hectare<br>MOP - 50.00 Kg Per Hectare<br>Urea - 104.91 Kg Per Hectare | SSP - 187.50 Kg Per Hectare<br>MOP - 50.00 Kg Per Hectare<br>Urea - 130.43 Kg Per Hectare |

MICRONUTRIENT FERTILIZER

Borax - 10.00 Kg Per Hectare

DISCLAIMER: OUR REPORT IS NOT TO BE REPRODUCED WHOLLY OR IN PART AND CANNOT BE USED AS EVIDENCE IN THE COURT OF LAW AND SHOULD NOT BE USED IN ANY ADVERTISING MEDIA WITHOUT OUR PRIOR WRITTEN APPROVAL. THE FERTILIZER RECOMMENDATION SHOWN IN THIS REPORT IS FOR A FULL SEASON OF THE SELECTED CROP.

HIMEDIA BHU-VISION
Krishi-RASTAA Soil Testing Device

Powered By KRISHITANTRA

**Fig. 5. Generated Soil Health Report**

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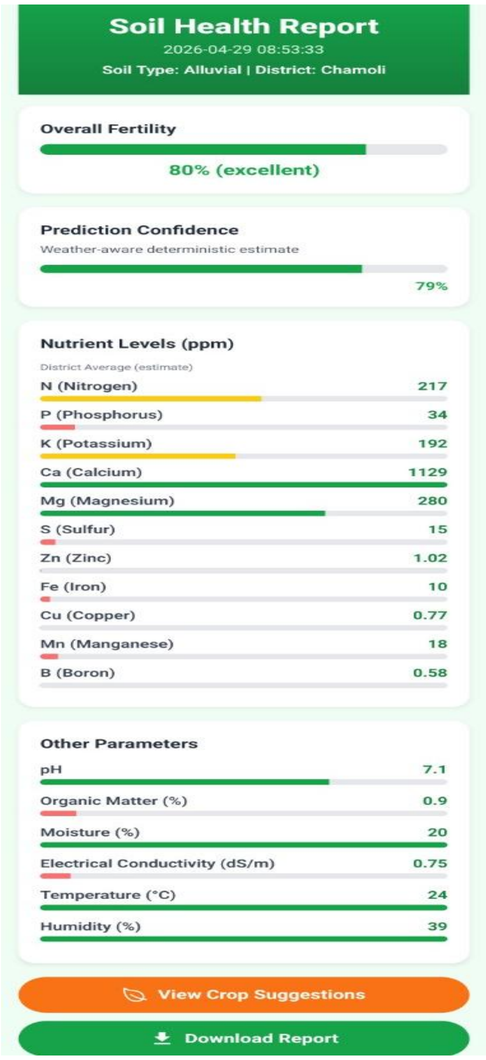


**Table 1. Comparison Between Laboratory Report and AI-Generated Report**

| Parameter | Laboratory Report (Fig:4) | Application Generated Report (Fig:5) | Observation |
|---|---|---|---|
| Soil Type | Alluvial | Alluvial | Correctly Identified |
| Nitrogen (N) | 227 kg/ha | 217 ppm | Approximate Match |
| Phosphorus (P) | 19.29 kg/ha | 34 ppm | Moderate Variation |
| Potassium (K) | 340 kg/ha | 192 ppm | Partial Similarity |
| pH Value | 6.63 | 7.1 | Near Comparable |
| Organic Matter | 0.79% | 0.9% | Similar Trend |
| Sulphur (S) | 29.29 mg/kg | 15 ppm | Moderate Difference |
| Zinc (Zn) | 0.66 mg/kg | 1.02 ppm | Acceptable Approximation |
| Iron (Fe) | >5 mg/kg | 10 ppm | Similar Estimation |
| Copper (Cu) | 0.29 mg/kg | 0.77 ppm | Approximate Prediction |
| Manganese (Mn) | 2.51 ppm | 18 ppm | Significant Variation |
| Boron (B) | 0.39 mg/kg | 0.58 ppm | Close Approximation |
| Soil Health | Good | 80% Excellent | Positive Correlation |

The comparison between the laboratory-generated soil report and the AI-generated report demonstrates that the proposed system is capable of producing approximate soil health estimations and nutrient predictions. Although certain variations exist due to the image-based estimation approach, the system successfully identifies overall soil characteristics and fertility trends. The generated results indicate that the proposed application can serve as a rapid and accessible preliminary soil advisory tool, especially in regions where laboratory testing facilities are limited.

Multiple soil samples collected from different locations and soil categories were tested and validated during the experimentation process. Repeated comparison with laboratory soil reports helped improve the consistency, reliability, and overall prediction capability of the proposed system.

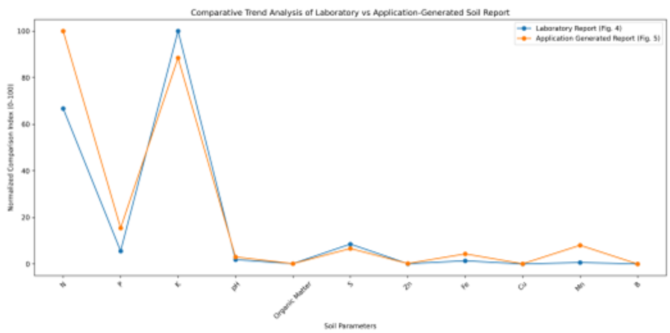


**Fig. 6. Comparative Trend Analysis of Laboratory and Application-Generated Soil Reports**

## 10. CONCLUSION

This project has taught us that useful agricultural AI is not only about model prediction. It is about creating a sound and interpretable decision pathway for the user. Our system currently offers this pathway: soil image analysis, nutrient advisory, crop recommendation, fertilizer advice, and policy assistance in one integrated application. Even with the current limitations, the system is a good step towards making smart farming assistance more accessible.

## 11. AUTHOR CONTRIBUTIONS

**Aayush Kumar Sati** and **Anurag Purohit: -** equally contributed to frontend development, backend implementation, AI model integration, experimentation, and research paper writing.

**Sandeep Singh Negi**: - contributed to dataset collection, research findings, and experimental support.

**Pankaj Bisht: -** contributed to dataset preparation, software testing, and research assistance.

**Mrs. Monika Bartwal**: - supervised the research work, provided technical guidance.

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