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Soil Composition Analysis with Crop and Inadequacy Suggestion

Dheeraj K R[1], Binu P Chacko[2], Deepthi M Pisharody[3]

[1,2,3]Postgraduate Department Of Computer Science,Prajyoti Niketan College,Thrissur,Kerala,India

Abstract:
As large populace of India primarily depends upon agriculture and related activities and it has a major role in Supporting the economy for its opulence. Any inadequacy of minerals and fallacious usage of agriculture tracts creates less-efficient utilization and abated yields. Most of the crop loss and less-efficiency of soil depend on the discrepancies of soil type and the crops.Thus the compatibility of soil and the crops is indispensable and to be ensured for sustainable agriculture.Most of agricultural land usages fall under the category in which the soil usage is unscientific and disparity of crop and soil exists. In such situations this inevitable compatibility is belied.In India there are different types of soils such as loamy, laterite,gravelly, peat et cetera having different compositions of minerals and there will be a deems-fit crops for each soil types. An appraisal Of soil composition will torch light to this notion and efficient utilization of soil will be ascertained.

The weilding of computerized actions in this scenario will ensure increased yields via digitization in agriculture. The use of Agricultural lands pursuant to the soil composition may help the farmers to produce enhanced yields and make a opulent economy.Analysis and suggesting the crops and inadequate minerals is sometimes banal and erroneous, thus replacing it by digital methods reduce human work on it.

Keywords-Support vector machine, Random forest, Artificial Intelligence, Ensemble methods,Soil nutrients, soil PH

1.INTRODUCTION

As India is a developing country in which 47% of populace primarily or indirectly depends on agricultural and related activities. Agriculture contributes to 18% of GDP of India according to the economic survey 2024. Thus, agriculture can be considered as the backbone of Indian economy by which subsequent sectors also flourish.

As invented technologies such as hydroponics and aquaponics are in embryonic stage in Indian agriculture and are inadequate as well as incompatible in supporting the large demographic need of India; thus soil can be considered as an important part of agriculture. Going to the basics, plants consume the essential nutrients such as nitrogen, potassium, phosphorous which are inevitable for its growth and reproduction, which they form from the soil.

Equal to the pertinence of the soil, so is the composition for better growth of plants, through which agricultural growth.

Incorporating artificial intelligence in finding the soil composition proportions and suggesting the inadequacies in each soil will promote a boom in agricultural produce. As India is between a large range of latitudes and has many geographical varieties or regions such as plains, plateaus, lakes, mountains, so is the variety of soil. Prominently India has loamy, laterite, peaty, clay soils in different regions. Growing right compatible crops pursuant to the composition of soil will promote flourished agriculture.

As agriculture and soil have manifold amount of data, integrating machine learning techniques in this regard forms the purpose of consolidating as well as bifurcating the data by foreseeing the increased agricultural productivity.

2.LITERATURE REVIEW

Artificial Intelligence and Machine Learning have significantly transformed modern agriculture by enabling data-driven crop recommendation systems. Kamilaris and Prenafeta-Boldú reviewed various AI applications in agriculture and highlighted the effectiveness of machine learning and deep learning techniques in agricultural prediction and decision-support systems [1]. Liakos et al. surveyed machine learning applications in agriculture and demonstrated that AI models can improve crop selection, yield prediction, and resource management through efficient analysis of environmental and soil data [2].

Machine learning algorithms such as Random Forest, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Naïve Bayes have been widely adopted for agricultural prediction tasks. Jeong et al. demonstrated that Random Forest models provide highly accurate crop yield predictions by effectively handling large and complex agricultural datasets [3]. Similar studies have shown that ensemble learning methods outperform traditional statistical approaches in crop classification and recommendation systems [4].

Crop recommendation systems utilize environmental factors such as temperature, rainfall, soil pH, and nutrient content to identify suitable crops for cultivation. Chlingaryan et al. reported that machine learning models can accurately predict crop performance and support agricultural decision-making through the analysis of historical agricultural data [5]. Their findings indicate that Random Forest and SVM consistently achieve higher prediction accuracy compared to simpler classification methods [6].

The integration of machine learning with precision agriculture technologies has further enhanced recommendation accuracy. Wolfert et al. highlighted the role of Big Data analytics, IoT devices, and AI techniques in enabling intelligent farming systems capable of processing large-scale agricultural information [7]. Shahhosseini et al. combined crop simulation models with machine learning algorithms and demonstrated significant improvements in crop prediction performance [8].

Advanced AI techniques such as deep learning and reinforcement learning have also been explored in agricultural applications. Elavarasan and Vincent proposed a deep reinforcement learning framework for agricultural prediction and reported improved adaptability to dynamic environmental conditions [9]. Deep learning approaches have shown promising results in handling complex agricultural datasets and supporting precision farming applications [10].

Recent studies have focused on integrating multiple machine learning models to improve reliability and recommendation effectiveness. Comparative analyses indicate that Random Forest generally achieves the highest accuracy due to its ensemble learning structure, while SVM provides competitive performance in high-dimensional datasets [11]. KNN and Naïve Bayes remain useful for baseline comparisons because of their simplicity and computational efficiency [12].

The growing availability of agricultural datasets, sensor technologies, and cloud computing platforms has accelerated the development of intelligent crop recommendation systems. Researchers continue to explore hybrid machine learning approaches that combine multiple algorithms to improve prediction accuracy and robustness [13]. These systems contribute to sustainable agriculture by helping farmers select crops that maximize productivity while minimizing resource wastage [14].

Overall, existing literature demonstrates that Artificial Intelligence and Machine Learning play a crucial role in agricultural decision support systems. The success of Random Forest, SVM, KNN, and Naïve Bayes models in previous studies provides a strong foundation for the development of the proposed Crop Recommendation System [15].

3. SOIL COMPOSITION AND COMMON INADEQUACIES

Soil is a complex and dynamic natural resource that plays a fundamental role in agriculture by providing nutrients, water, and support to plants. The effectiveness of soil in sustaining crop growth is determined by its composition, which includes a balance of physical, chemical, and biological components. Understanding the key elements of soil composition is essential for identifying inadequacies and managing them effectively, especially with the assistance of modern technologies like AI.

A) Key Components of Soil Composition

1.Mineral Content

Soil is primarily composed of minerals derived from the weathering of rocks. These minerals include sand, silt, and clay, which define the soil's texture and influence its water retention and drainage capacity.The ideal agricultural soil, loam, is a balanced mixture of all three.

2.Organic Matter

Comprising decomposed plant and animal residues, organic matter improves soil structure, water retention, and microbial activity.It also enhances the soil's nutrient-holding capacity.

3.Soil pH

Soil pH indicates the acidity or alkalinity of the soil. It significantly affects nutrient availability and microbial activity.Most crops prefer a pH between 6.0 and 7.5, but this can vary depending on the crop species.

4.Macronutrients and Micronutrients

Macronutrients like nitrogen (N), phosphorus (P), and potassium (K) are essential in large quantities.Micronutrients, such as zinc (Zn), iron (Fe), and manganese (Mn), are required in smaller amounts but are equally critical for healthy plant development.

5.Moisture Content

Adequate soil moisture is necessary for nutrient uptake and metabolic processes in plants.Water retention capacity varies based on soil texture and organic matter.

6.Microbial Life

Healthy soil contains diverse microbial populations that support nutrient cycling and disease suppression.

B) Common Soil Inadequacies

Despite the natural richness of soil, many regions face issues that limit agricultural productivity. These inadequacies can often be detected through soil testing or AI-driven sensors.

Inadequacy Cause Impact on Crops:

- Nitrogen Deficiency Leaching, overuse of crops without rotation Stunted growth, yellowing of leaves
- Phosphorus Deficiency Low organicmatter, erosion Poor root development, delayed maturity
- Potassium Deficiency Sandy soils, heavy leaching Weak stems, leaf discoloration

- Low pH (Acidic Soil) High rainfall, certain fertilizers Reduced nutrient availability
- High pH (Alkaline Soil) Overliming, saline irrigation Micronutrient deficiencies
- Poor Soil Structure Compaction, lack of organic matter Poor aeration and water infiltration
- Low Organic Matter Intensive farming, burning crop residues Decreased fertility, erosion

C) The Need for Early Detection

Early detection of these deficiencies is vital for sustainable agriculture. Traditionally, this has involved manual soil sampling and laboratory testing, which is time-consuming and localized. Modern AI-based tools now enable:

- Real-time detection of nutrient deficiencies using sensor networks or hyperspectral imaging.
- Predictive models to forecast degradation trends.
- Automated crop and fertilizer recommendations based on historical and live soil data.

4.ROLE OF AI IN SOIL COMPOSITION ANALYSIS

The integration of Artificial Intelligence (AI) into soil composition analysis has marked a paradigm shift in agricultural technology. Traditionally, soil health assessments relied on periodic manual sampling and laboratory testing. However, these methods are often labor-intensive, time-consuming, and spatially limited. AI offers scalable, data-driven alternatives that can analyze vast datasets quickly and accurately, improving both efficiency and decision-making in agriculture.

A) Data Sources for AI in Soil Analysis

- AI systems rely on various input data types to assess soil conditions:
- Satellite Imagery: Captures large-scale data on soil moisture, vegetation health, and terrain.
- IoT Sensors: Ground-based sensors collect real-time data on pH, moisture, temperature, and electrical conductivity.
- Drones: Equipped with multispectral and hyperspectral cameras to detect soil characteristics.
- Soil Databases: Historical soil data repositories (e.g., SoilGrids, USDA NRCS Soil Survey) are used to train predictive models.

B) AI Techniques Applied

Several AI methodologies are employed:

- Machine Learning (ML): Algorithms such as Decision Trees, Random Forests, and Support Vector Machines are trained on soil data to classify soil types and predict deficiencies.
- Neural Networks: Deep learning models can handle non-linear relationships between multiple soil variables to generate accurate predictions.
- Computer Vision: Used in conjunction with drones and satellites to analyze soil texture and detect erosion patterns or nutrient stress.

C) Outputs and Applications

AI-driven soil analysis produces actionable outputs such as:

- Spatial soil fertility maps.
- Site-specific recommendations for nutrient application.
- Early warning systems for soil degradation.

5.AI-BASED CROP RECOMMENDATION SYSTEMS

Once soil composition has been analyzed, AI can also be used to recommend optimal crops suited to the current soil and climatic conditions. This approach, called precision agriculture, aims to maximize yield while minimizing resource use and environmental impact.

A) How It Works

AI systems synthesize various types of data to suggest suitable crops:

- Soil Profile: Nutrient levels, texture, and organic matter.
- Climate Data: Rainfall, temperature patterns, and seasonal variability.
- Topography: Elevation, slope, and drainage conditions.
- Historical Yields: Past performance of crops on similar soils.

B) Recommendation Algorithms

- Collaborative Filtering: Similar to what's used in Netflix or Amazon, this method suggests crops based on success in similar farms.
- Rule-Based Systems: Uses expert knowledge (e.g., if pH < 6.0, recommend legumes).
- Predictive Models: ML models trained on crop-soil-yield data to predict the best crop for a given plot.

C) Benefits

- Reduces trial-and-errorplanting.g
- Improves profitability for farmers.
- Promotes sustainable land use by avoiding over-farming unsuitable crops.

6.CHALLENGES AND LIMITATIONS

Despite the transformative potential of Artificial Intelligence in agriculture, several challenges hinder its large-scale adoption, particularly in developing regions like India. One of the foremost limitations is data availability and quality. Many agricultural zones lack reliable and consistent soil data, making it difficult to train accurate machine learning models. Additionally, sensors and IoT devices that gather real-time data are prone to malfunction, and when they fail or produce noisy outputs, the predictions generated by AI systems can become unreliable. Technical barriers also exist — many models suffer from overfitting when trained on small or biased datasets, resulting in poor generalization to new regions or crop varieties.

Furthermore, there is a lack of interoperability between AI tools created by different developers, which limits integration into a unified decision-making system. Beyond the technical domain, socioeconomic factors play a substantial role. The high initial cost of AI systems, including sensors, drones, and computing infrastructure, makes them inaccessible to many smallholder farmers. Moreover, the digital divide, especially in rural areas, results in limited access to technology and insufficient technical literacy. These challenges must be addressed through policy support, targeted subsidies, open-source tools, and inclusive education to ensure AI truly benefits the grassroots level of agriculture.

7.RESULTS AND DISCUSSION

The results obtained from testing and evaluation demonstrate the effectiveness of the proposed Soil Composition Analysis with Crop Suitability and Inadequacy Suggestion System. Four machine learning models, namely Random Forest, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Naïve Bayes, were trained and evaluated using the prepared agricultural dataset. Among these models, Random Forest achieved the highest accuracy of approximately 96%, followed by SVM with 95%, KNN with 85%, and Naïve Bayes with 82%. The superior performance of Random Forest can be attributed to its ensemble learning capability, which effectively captures complex relationships among soil nutrients, pH, temperature, rainfall, and crop suitability.

Manual validation using separate testing and validation datasets further confirmed the reliability of the generated recommendations. The system consistently produced suitable crop suggestions for different soil conditions while also identifying nutrient inadequacies. The results indicate that integrating multiple machine learning models with soil composition analysis can significantly improve agricultural decision-making and support farmers in selecting the most appropriate crops for cultivation.

8.CONCLUSION AND FUTURE WORK

The reviewed literature clearly establishes the growing significance of Artificial Intelligence in soil composition analysis and crop recommendation systems. Among the various models, Convolutional Neural Networks (CNNs) dominate image-based classification tasks due to their ability to capture spatial features from soil and remote sensing imagery. Hybrid models, such as CNN-LSTM and CNN-Autoencoder-Random Forest, demonstrate superior performance by integrating spatial, temporal, and non-linear relationships in soil data.

Moreover, the emergence of Transformer-based architectures and Transfer Learning approaches addresses challenges like limited training data and domain shifts. These advancements have enabled models to achieve high accuracy (>90%) in predicting crucial soil properties such as texture, moisture, organic carbon, and pH. In parallel, GUI-based and mobile-integrated AI systems have improved accessibility and usability for end users like farmers and agronomists.

Despite their promise, challenges such as data standardization, model explainability, and regional adaptation remain. However, the overall direction of research indicates a strong movement towards scalable, intelligent, and user-friendly soil analytics, paving the way for more sustainable and precise agricultural practices.

The proposed Soil Composition Analysis with Crop Suitability and Inadequacy Suggestion System provides a strong foundation for intelligent agricultural decision-making. Future enhancements may include the integration of real-time weather data and satellite-based environmental information to improve prediction accuracy. The system can be extended to provide multiple crop recommendations ranked according to suitability scores rather than a single recommendation. Integration with IoT-based soil sensors would enable automatic collection of soil parameters and continuous monitoring. Additional machine learning and deep learning models may further enhance performance. Mobile application support and multilingual interfaces can also improve accessibility and adoption among farmers across different regions.

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