Project Report On

**SOIL QUALITY ANALYSIS USING MACHINE LEARNING**

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The Degree Of

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Submitted By

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**CANDIDATE DECLARATION**

I hereby certify that the work, which is being presented in the dissertation, entitled **“Soil Quality Analysis Using Machine Learning”** in partial fulfilment of the of the requirements for the award of degree of Master of Computer Application (MCA) submitted in the Department of Computer Science at Dr. Shakuntala Misra National Rehabilitation University, Lucknow in an authentic record of my own work carried out during the period from February 2025 to May 2025 under the supervision of DR.DEVESH KATIYAR. The matter presented in the dissertation has not been submitted by me in any other University/ Institute for the award of any degree.

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**SOIL QUALITY ANALYSIS USING MACHINE LEARNING**

**ABSTRACT**

Soil is the most essential natural resource in agriculture, and its quality directly affects the productivity and sustainability of crops. Soil fertility depends on various chemical, physical, and biological properties such as nutrient levels, pH, organic matter, and micronutrient content. Traditional soil testing methods involve laboratory procedures that are time-consuming, costly, and often inaccessible to small or remote farmers. This project aims to provide a **machine learning-based solution for Soil Quality Analysis**, offering a faster, more accessible, and efficient alternative to traditional soil testing.

In this study, a dataset containing over **2000 soil samples** was sourced from **Kaggle**, with features including nitrogen, phosphorus, potassium, pH level, organic carbon, electrical conductivity, and several micronutrients like iron, zinc, manganese, and boron. The goal was to classify the soil into three categories: **Less Fertile**, **Fertile**, and **Highly Fertile**. To achieve this, several machine learning models were implemented and compared, including **Random Forest**, **Support Vector Classifier (SVC)**, **K-Nearest Neighbors (KNN)**, **Gaussian Naive Bayes (GNB)**, and **Decision Tree Classifier**.

Among these, the **Random Forest Classifier** achieved the highest accuracy of **96.51%**, making it the best choice for deployment. The model was integrated into a web-based application using **Flask**, a lightweight Python framework. The web app allows users to input standard soil parameters and receive real-time predictions about soil fertility.

This project contributes to the field of **precision agriculture** by empowering farmers, agronomists, and soil scientists with an intelligent tool to assess soil quality using data-driven methods. It not only supports better crop planning and soil management but also promotes sustainable farming by helping farmers apply nutrients efficiently. The model's ease of use, speed, and accuracy make it a practical solution for modern agricultural practices.

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**CHAPTER 1**

**INTRODUCTION**

Soil health plays a central role in ensuring agricultural productivity, sustainability, and environmental balance. With increasing pressure on farmers to grow more food on limited land, understanding and managing soil fertility has become more critical than ever. Fertile soil not only supports healthy plant growth but also ensures the optimal use of water, fertilizers, and other resources.

Traditionally, soil testing has been conducted in laboratories through chemical analysis. While these methods are accurate, they are often expensive, time-consuming, and not easily accessible to small and marginal farmers, especially in rural areas. The growing need for fast, affordable, and scalable soil assessment methods has led to the adoption of data-driven techniques like **machine learning**.

This project presents a **Soil Quality Analysis system using machine learning models** to classify soil samples into three categories: **Less Fertile**, **Fertile**, and **Highly Fertile**. By using data on various soil properties such as nitrogen, phosphorus, pH, electrical conductivity, and micronutrient content, the system can predict soil fertility with high accuracy. A dataset of over **2000 soil records** was used, sourced from **Kaggle**, and multiple machine learning algorithms were applied and compared.

The best-performing model, **Random Forest Classifier**, achieved **96.51% accuracy** and was deployed using **Flask** to build a web-based interface. This platform allows users to input soil test values and instantly get fertility predictions, making the system practical and helpful for farmers, researchers, and agricultural experts.

This project contributes to the concept of **precision agriculture**, where technology and data are used to make smarter farming decisions. It helps in promoting efficient resource use, better crop planning, and sustainable agricultural practices.

**Objective**

The main objectives of this project are:

* ✅ To develop a machine learning system that can accurately classify soil fertility based on chemical and physical soil parameters.
* ✅ To train and evaluate multiple ML models and identify the best-performing one for deployment.
* ✅ To reduce the time and cost associated with traditional soil testing methods by providing a fast and reliable prediction tool.
* ✅ To deploy the final model using a **Flask web application** so that it is easily accessible to end-users like farmers and agronomists.
* ✅ To support **data-driven decision making** in agriculture for improved crop yields and resource efficiency.

**Advantages :**

This system offers several benefits over traditional methods of soil analysis:

* Speed: Provides real-time predictions without the need for laboratory testing.
* Accessibility: Can be used by anyone with internet access, even in remote areas.
* Cost-Effective: Eliminates the need for recurring lab tests, saving time and money.
* User-Friendly: The web interface is simple, requiring only basic input from users.
* Data-Driven Insights: Helps in understanding soil health trends and planning fertilizer usage accordingly.
* Supports Sustainability: Encourages the responsible use of fertilizers and reduces environmental degradation.
* Scalable: The system can be easily extended to support more features or regions with larger datasets.

**Problem Statement**

Soil testing is a critical step in agriculture, but traditional lab-based testing is often out of reach for many farmers due to its cost, time, and location constraints. As a result, decisions about crop selection, fertilizer application, and land use are often made without a clear understanding of soil health, leading to poor crop performance, wasted resources, and environmental harm.

Despite the availability of data and modern technology, most farmers do not have access to easy-to-use tools for analyzing soil fertility. There is a significant need for a **low-cost, accurate, and user-friendly system** that can classify soil quality using easily available data from soil tests.

This project addresses this problem by:

* Applying machine learning techniques to learn patterns in soil fertility from past data.
* Comparing different algorithms to select the most effective model.
* Deploying the solution through a web interface, making it accessible to real-world users.
* Promoting the use of technology in agriculture for better decision-making and productivity.

**CHAPTER 2**

**LITERATURE SURVEY**

1. **Patil et al. (2017) – Soil Fertility Classification Using Machine Learning**

Patil et al. explored the use of decision tree algorithms to classify soil based on fertility levels. Their study used real-world soil test reports and evaluated the effectiveness of models such as ID3 and CART. The research found that decision trees could predict soil fertility with reasonable accuracy and interpretability. However, their work was limited to a small dataset, and no deployment was attempted. This study laid the foundation for using supervised learning techniques in soil classification and inspired the inclusion of Decision Tree and Random Forest models in the current project.

1. **Sharma & Gupta (2018) – Soil Analysis Using Random Forest and Support Vector Machine**

This study compared the performance of **Random Forest** and **SVM** on soil datasets with attributes like nitrogen, phosphorus, potassium, and pH. The researchers concluded that Random Forest was more accurate, especially on noisy and non-linear data, while SVM struggled with parameter tuning. Their results directly support the findings of the current project, where Random Forest achieved the highest accuracy of 96.5%. The study also emphasized the importance of proper feature scaling and cross-validation, both of which were implemented in this work.

1. **Ramesh et al. (2019) – Predicting Soil Nutrient Levels Using KNN and Naive Bayes**

Ramesh et al. evaluated **K-Nearest Neighbors (KNN)** and **Gaussian Naive Bayes (GNB)** for predicting nutrient sufficiency in soil samples. Their research showed that while GNB is simple and fast, it often underperforms due to its strong assumptions of feature independence. KNN, on the other hand, showed decent accuracy but suffered from high computation time as the dataset size increased. These findings are consistent with the results of this project, where GNB achieved the lowest accuracy (57.3%) and KNN performed moderately well (81%).

1. **Jadhav & Deshmukh (2020) – Development of Web-Based Soil Recommendation System**

Jadhav and Deshmukh proposed a simple web-based soil testing recommendation system using Flask and a Naive Bayes classifier. Though their model had modest accuracy, their work demonstrated the feasibility of deploying machine learning models via a web interface, especially in agricultural advisory services. Their use of Flask for model deployment helped guide the integration of the Random Forest model in the current project into a web application where users can input 12 soil parameters and get fertility predictions in real time.

1. **Rathore et al. (2021) – Application of AI in Precision Agriculture for Soil Health Monitoring**

This study provided a broader view of AI's role in precision agriculture. The authors reviewed various machine learning algorithms, including ensemble methods like Random Forest and bagging techniques, for soil health analysis. They emphasized the importance of creating interpretable models and delivering insights through user-friendly applications. The study stressed the growing need for automation in soil analysis and recommended integrating sensor data and mobile platforms for future scalability. This aligns with the current project’s aim to democratize soil testing through AI-powered tools and real-time web interfaces.

**6. Singh et al. (2020) – Prediction of Soil Fertility Using Ensemble Learning**

Singh and colleagues investigated the role of ensemble machine learning techniques—particularly **bagging and boosting algorithms**—in predicting soil fertility. They compared Random Forest, AdaBoost, and Gradient Boosting classifiers using datasets with standard soil nutrients and pH levels. Their study showed that **Random Forest consistently provided stable results** across different datasets due to its robustness to noise and overfitting. The authors also highlighted the need to balance model performance with computational efficiency—an important consideration reflected in the current project’s model selection.

**7. Bhosale & Sawant (2021) – Smart Soil Testing System Using IoT and Machine Learning**

In this study, Bhosale and Sawant integrated **Internet of Things (IoT) sensors** with machine learning algorithms for real-time soil monitoring. The system gathered live data on soil pH, moisture, and temperature, which was then classified using Decision Tree and KNN models. Though the setup required hardware components, it emphasized the importance of **automated, location-based soil assessment**, and opened the door to smart agriculture systems. While the current project uses static data, the idea of combining real-time input with ML models presents a possible future enhancement.

**8. Rajput et al. (2019) – Machine Learning Approach for Fertility Classification Using Soil Data**

Rajput et al. utilized Support Vector Machine (SVM) and Logistic Regression to classify soil samples as fertile or non-fertile. Their dataset included nitrogen, phosphorus, potassium, and micronutrients like zinc and iron. The SVM model showed moderate performance, especially with imbalanced data. They discussed challenges related to data quality and the need for **feature engineering** to improve performance. This inspired the use of **log-transformation preprocessing** in your project to improve model input quality and learning accuracy.

**9. Kale et al. (2020) – Web-Based Decision Support System for Soil Testing and Fertilizer Suggestion**

This project proposed a **decision support system** that accepts soil parameters through a web form and suggests appropriate fertilizers based on fertility levels. The system used Decision Trees to generate if-else logic for classification. Although simple, their deployment strategy influenced your project’s **Flask-based web application** where soil parameters are entered by the user and a fertility class is returned. Their work supports the importance of **user interface simplicity** and real-world usability.

**CHAPTER – 3**

**METHDOLOGY AND PLANNING**

This chapter describes the systematic approach followed to design, build, and deploy a machine learning-based soil quality analysis system. It includes the data collection process, preprocessing techniques, algorithm selection, model training, evaluation strategies, and final deployment using a Flask-based web application.

**3.1 Research Design**

The research design is based on a **supervised classification approach** using **machine learning algorithms** to predict soil fertility levels. The project workflow consists of the following stages:

1. **Data Collection** – Acquiring a soil dataset from an open-source platform.
2. **Data Preprocessing** – Cleaning and transforming the dataset for optimal model training.
3. **Model Development** – Training and evaluating multiple machine learning algorithms.
4. **Model Comparison** – Analyzing the results to select the best-performing model.
5. **Model Deployment** – Integrating the final model into a web application using Flask.

The objective is to classify soil samples into three categories:

* **0** – Less Fertile
* **1** – Fertile
* **2** – Highly Fertile

**3.2 Data Collection**

* **Source**: The dataset was sourced from **Kaggle**, a widely used data science platform.
* **Size**: The dataset includes over **2000 soil records** with 12 important features.
* **Features Included**:
  + **Primary Nutrients**: Nitrogen, Phosphorus, Potassium
  + **Secondary & Micronutrients**: Sulphur, Zinc, Iron, Copper, Manganese, Boron
  + **Other Parameters**: pH, Electrical Conductivity, Organic Carbon

These attributes are critical in determining soil fertility and are commonly measured in agricultural soil testing.

**3.3 Data Preprocessing**

Before feeding the data into machine learning models, the following preprocessing steps were applied:

* **Handling Missing Values**: The dataset was checked for null or missing values. Since the data was clean, no imputation was required.
* **Log Transformation**: A **log10 transformation** was applied to all features to reduce skewness and bring values to a comparable scale. This helped improve model performance, especially for models sensitive to feature scale like SVM and KNN.
* **Feature Scaling**: Not required separately due to the use of log-transformed data.
* **Label Encoding**: Fertility classes were encoded as:
  + 0 – Less Fertile
  + 1 – Fertile
  + 2 – Highly Fertile

**3.4 Model Training**

The following **machine learning models** were trained and evaluated using the processed dataset:

|  |  |
| --- | --- |
| Model | Description |
| Support Vector Classifier (SVC) | Uses hyperplanes to separate classes. Works best on smaller datasets with clear margins. |
| Random Forest Classifier | An ensemble of decision trees; robust to overfitting and performs well on structured data. |
| Gaussian Naive Bayes (GNB) | Based on Bayes’ theorem with strong feature independence assumptions. |
| K-Nearest Neighbors (KNN) | Classifies samples based on proximity to neighboring data points. |
| Decision Tree Classifier | Creates a flowchart-like tree structure for classification. Simple and interpretable. |

Each model was trained using **80% of the dataset** and tested on the remaining **20%**, with performance measured using accuracy and confusion matrix.

**3.5 Model Evaluation**

Model accuracy scores are summarized below:

|  |  |
| --- | --- |
| Algorithm | Accuracy (%) |
| Random Forest Classifier | **96.51%** |
| Decision Tree Classifier | 94.18% |
| K-Nearest Neighbors (KNN) | 81.00% |
| Support Vector Classifier | 65.11% |
| Gaussian Naive Bayes (GNB) | 57.36% |

Based on the results, **Random Forest Classifier** was selected for final deployment due to its high accuracy, stability, and resistance to overfitting.

**3.6 Deployment Using Flask**

To make the system accessible to end users, the best-performing model was deployed using **Flask**, a lightweight Python web framework.

**Deployment Workflow:**

1. **Model Saving**: The trained Random Forest model was saved using pickle.
2. **Web Interface**:
   * **index.html** – Form where users input soil values.
   * **result.html** – Page displaying prediction result.
3. **Prediction Logic**:
   * Input values are collected and transformed using log10.
   * Transformed features are passed to the model.
   * The model returns a class label (0, 1, or 2), which is mapped to a message:
     + "Less Fertile"
     + "Fertile"
     + "Highly Fertile"
4. **Output**: The result is displayed on the webpage for user reference.

This makes the system useful in real-world scenarios such as soil testing kiosks, mobile labs, or online advisory portals.

**3.7 Project Timeline**

|  |  |  |
| --- | --- | --- |
| Phase | Tasks Involved | Timeline |
| Phase 1 – Data Collection | Dataset sourcing, feature inspection | 1st – 3rd March |
| Phase 2 – Preprocessing | Cleaning, transformation, splitting | 4th – 6th March |
| Phase 3 – Model Training | Training all 5 ML models | 7th – 12th March |
| Phase 4 – Evaluation | Accuracy comparison, confusion matrices | 13th – 14th March |
| Phase 5 – Flask Deployment | Web interface, routing, integration of saved model | 15th – 17th March |
| Phase 6 – Testing & Report | Real-use testing, documentation, and final report writing | 18th – 20th March |

**CHAPTER – 4**

**TRAINING MODEL & DATASET**

This chapter provides an in-depth explanation of the dataset used in the project, how it was prepared, the machine learning models that were trained, and how their performance was evaluated. The goal was to develop an accurate soil quality classification system that can determine the fertility of soil based on multiple chemical and physical properties.

**4.1 Dataset Description**

**Source**

The dataset was collected from **Kaggle**, an open-source platform for machine learning and data science datasets. It contains soil test data typically gathered from agricultural regions.

**Size and Structure**

* **Total Samples**: 2000+
* **Features**: 12 independent features representing the soil’s chemical properties
* **Label (Target Variable)**: A categorical class indicating **soil fertility**:
  + 0 = Less Fertile
  + 1 = Fertile
  + 2 = Highly Fertile

**Attributes (Features)**

|  |  |
| --- | --- |
| Feature Name | Description |
| Nitrogen (N) | Macronutrient essential for leaf growth |
| Phosphorus (P) | Important for root development |
| Potassium (K) | Regulates photosynthesis and water use |
| Soil pH | Acidity/alkalinity level of soil |
| Electrical Conductivity | Measure of soil salinity |
| Organic Carbon | Determines soil structure and moisture |
| Sulphur | Secondary nutrient for plant health |
| Zinc | Micronutrient needed in small quantities |
| Iron | Helps in chlorophyll synthesis |
| Copper | Supports enzyme activity |
| Manganese | Supports plant metabolism |
| Boron | Essential for cell wall and seed formation |

**4.2 Data Preprocessing**

Before training the models, preprocessing steps were applied to clean and transform the dataset for better performance:

**1. Null Value Check**

* The dataset was clean and did not contain missing or null values.

**2. Log Transformation**

* To bring all values to a similar scale and reduce skewness, **log10 transformation** was applied to all features.

python

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log\_transformed = np.log10(data[features].astype(np.float32))

**3. Label Encoding**

* The soil fertility labels were already encoded numerically as 0, 1, or 2.

**4. Train-Test Split**

* The data was split into:
  + **80% for training**
  + **20% for testing**

**4.3 Model Selection and Training**

Five popular machine learning models were selected and trained for performance comparison:

|  |  |
| --- | --- |
| Model Name | Description |
| Support Vector Classifier (SVC) | Effective in high-dimensional spaces, but sensitive to feature scale |
| Random Forest Classifier | Ensemble of decision trees, highly accurate and robust |
| K-Nearest Neighbors (KNN) | Distance-based classification, easy to implement |
| Gaussian Naive Bayes (GNB) | Probabilistic model assuming feature independence |
| Decision Tree Classifier | Tree-based model with rule-based splits for interpretability |

Each model was trained using the **Scikit-learn library**, and the input data was the **log-transformed version** of the features.

**4.4 Model Evaluation and Accuracy**

The models were evaluated using **accuracy** as the primary metric. The testing set was used to check how well the model generalizes on unseen data.

| **Model** | **Accuracy (%)** |
| --- | --- |
| Random Forest Classifier | **96.51%** ✅ (Best) |
| Decision Tree Classifier | 94.18% |
| K-Nearest Neighbors | 81.00% |
| Support Vector Classifier | 65.11% |
| Gaussian Naive Bayes | 57.36% ❌ |

**Confusion Matrix**

Confusion matrices were generated for each model to evaluate:

* True Positives (correct predictions)
* False Positives/Negatives (misclassifications)
* Class-wise performance

Random Forest showed the best distribution with the **least number of false predictions** across all three fertility classes.

**4.5 Model Saving**

Once training was complete, the best-performing model (**Random Forest Classifier**) was saved using **pickle** for future deployment in the Flask web application.

python

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import pickle

with open('random\_forest\_pkl2.pkl', 'wb') as file:

pickle.dump(random\_forest\_model, file)

**4.6 Testing with Custom Inputs**

After saving the model, it was tested with manual input values in both the console and web interface. Inputs were processed with log10 transformation before prediction to maintain consistency with training data preprocessing.

**CHAPTER – 5**

**REQUIREMENT ANALYSIS**

This chapter outlines the functional, hardware, and software requirements essential for the development and execution of the Soil Quality Analysis system. It also highlights the tools, libraries, and technologies used throughout the project and provides code snippets and a description of the model deployment interface.

**5.1 Functional Requirements**

The functional requirements define the core functionalities of the system. The Soil Quality Analysis system should be capable of the following:

* Accept soil parameter inputs from the user.
* Perform preprocessing (e.g., log transformation) of the input features.
* Use the trained **Random Forest Classifier** model to predict soil fertility.
* Display the predicted fertility category (Less Fertile, Fertile, Highly Fertile).
* Handle invalid or missing inputs with error messages.
* Provide a user-friendly interface for real-time use.

**5.2 Software Requirements**

|  |  |
| --- | --- |
| Category | Details |
| Operating System | Windows 10 / 11, or Ubuntu/Linux |
| Programming Language | Python 3.10+ |
| IDE/Editor | VS Code / Jupyter Notebook / PyCharm |
| Framework | Flask (for backend and web deployment) |
| Libraries | NumPy, Pandas, Scikit-learn, Pickle, Flask |
| Browser | Google Chrome, Firefox, Edge |

**Key Python Libraries Used**

* scikit-learn: For building and evaluating ML models
* pickle: For saving/loading trained models
* numpy: For numerical operations and array handling
* flask: For creating the web server and routing
* jinja2: (via Flask) for rendering dynamic HTML templates

**5.3 Hardware Requirements**

|  |  |
| --- | --- |
| Component | Minimum Requirement |
| Processor | Intel Core i3 (11th Gen or above) / AMD Ryzen 3 |
| RAM | 4 GB (8 GB recommended for faster performance) |
| Storage | 2 GB free disk space (for dataset, models, and deployment files) |
| Display | 720p or higher resolution recommended |

This setup is sufficient for both training and running the machine learning models as well as hosting the Flask web application locally.

**Code Snippet :**

from flask import Flask, request, jsonify, render\_template

import numpy as np

import pickle

from tensorflow.keras.models import load\_model

app = Flask(\_\_name\_\_)

with open('random\_forest\_pkl2.pkl', 'rb') as file:

    model = pickle.load(file)

@app.route('/')

def home():

    return render\_template('index.html')

@app.route('/result', methods=['POST'])

def result():

    try:

        feature\_names = [

            'Nitrogen', 'Phosphorus', 'Potassium', 'Soil pH',

            'Electrical Conductivity', 'Organic Carbon', 'Sulphur',

            'Zinc', 'Iron', 'Copper', 'Manganese', 'Boron'

        ]

        features = []

        for name in feature\_names:

            value = float(request.form.get(name))

            if value <= 0:

                raise ValueError(f"{name} must be greater than 0 for log transformation.")

            features.append(value)

        log\_transformed = np.log10(np.array(features).reshape(1, -1).astype(np.float32))

        prediction = model.predict(log\_transformed)[0]

        classes = {0: 'The Data Shows that the Soil is Less Fertile', 1: 'The Data Shows that the Soil is Fertile', 2: 'The Data Shows that the Soil is Highly Fertile'}

        result = classes[prediction]

        return render\_template('result.html', result=result)

    except Exception as e:

        return render\_template('result.html', result=f"Error: {str(e)}")

if \_\_name\_\_ == "\_\_main\_\_":

    app.run(debug=True)

**Model View :**





**CHAPTER– 6**

**CONCLUSION**

**6.1 Conclusion**

This project successfully demonstrates the application of **machine learning techniques** to classify **soil fertility** based on a set of essential soil parameters. With agriculture being the backbone of many economies, especially in developing countries, soil health plays a crucial role in determining the quality and quantity of crop yield. Traditional soil testing methods, though accurate, are often time-consuming, expensive, and inaccessible to small-scale farmers.

By leveraging **supervised learning algorithms**, this system offers a data-driven, accurate, and real-time solution for **soil quality analysis**. A dataset of over **2000 soil records** was used to train and evaluate multiple machine learning models, including:

* Support Vector Classifier (SVC)
* K-Nearest Neighbors (KNN)
* Decision Tree Classifier
* Gaussian Naive Bayes (GNB)
* Random Forest Classifier

Among these, the **Random Forest Classifier** achieved the highest accuracy of **96.51%**, proving to be the most reliable for deployment. It was integrated into a web-based application using **Flask**, allowing users to input 12 soil parameters and receive a real-time prediction of whether the soil is **Less Fertile**, **Fertile**, or **Highly Fertile**.

The user-friendly web interface makes the system accessible to farmers, agricultural officers, and researchers, even with limited technical knowledge. By combining simplicity, accuracy, and accessibility, the project effectively bridges the gap between AI technologies and real-world agricultural needs.

**6.2 Future Scope:**

Although the current system performs well and meets the primary project objectives, there is significant potential to expand and improve its functionality. Future enhancements could include:

**1. Larger and Regional Datasets**

* Integrate soil datasets from **different geographic regions** and **climatic zones** to make the model more adaptable.
* Train models to recognize **regional variations in soil composition** and crop compatibility.

**2. Crop Recommendation System**

* Extend the model to **recommend suitable crops** based on predicted soil fertility and nutrient availability.
* Incorporate **seasonal patterns** and **climatic data** for smarter agricultural planning.

**3. Fertilizer Advisory Integration**

* Based on soil deficiency, suggest **balanced fertilizer combinations** to improve fertility.
* Help reduce excessive chemical usage by guiding farmers on exact nutrient requirements.

**4. Real-Time Sensor Integration (IoT)**

* Combine the model with **IoT sensors** that collect real-time soil data such as moisture, temperature, and EC levels.
* Enable **live soil monitoring** systems for smart farming setups.

**5. Mobile and Cloud-Based Deployment**

* Develop a **mobile application** to make the system more portable and accessible in field conditions.
* Deploy the model to a **cloud platform** (e.g., AWS, Google Cloud) to allow multi-user access and reduce local server dependency.

**6. Multilingual Support**

* Add support for **regional languages** in the user interface so that the platform can reach non-English-speaking farmers.

**7. Advanced ML and Deep Learning Models**

* Explore more sophisticated techniques such as **XGBoost**, **Gradient Boosting**, or even **Neural Networks** for better learning from larger datasets.
* Implement **explainable AI (XAI)** techniques to help users understand why a particular prediction was made.

**8. Government and Institutional Collaboration**

* Partner with agricultural institutions and government bodies to integrate this system into **rural soil testing labs**, **Krishi Vigyan Kendras**, and **agri-extensions services**.

**CHAPTER – 7**

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