SoilStream - A Smart Solar-Powered IoT System for Real-Time Soil Moisture Monitoring and Automated Irrigation

Problem Definition

SoilStream aims to address inefficient water usage, unpredictable weather conditions, and crop health challenges by providing farmers with real-time monitoring, smart irrigation, and AI-driven insights for improved productivity and sustainable agriculture.

Introduction

SoilStream is a smart agriculture system that:

- Encourages efficient farming by providing real-time soil monitoring and automated irrigation using IoT sensors.
- Leverages machine learning to predict rainfall and help farmers make better irrigation decisions.
- Helps reduce water wastage and improve crop yield through crop-specific soil and water recommendations.
- Offers features such as soil moisture tracking, smart irrigation control, weather prediction, and AI-based pest and disease detection using image analysis.

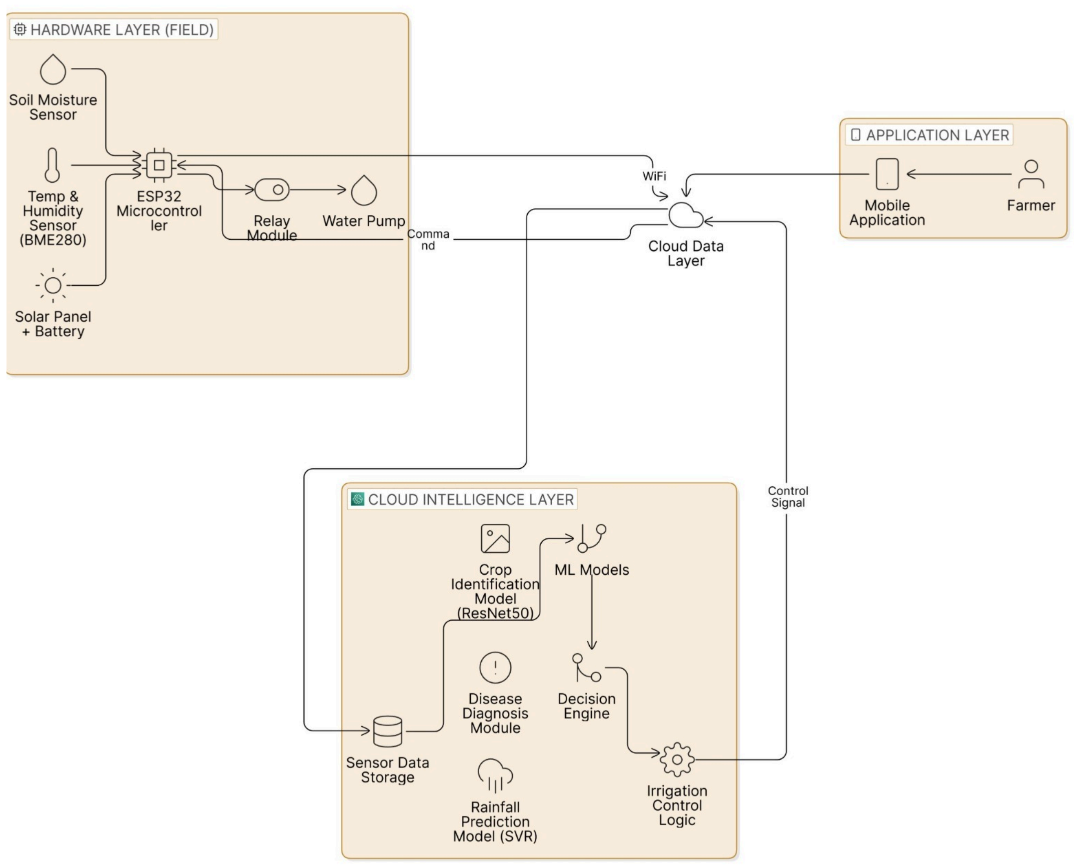
Scope

- SoilStream can be applied in small farms, organic fields, and research plots, offering smart irrigation and crop monitoring solutions.
- SoilStream is designed for small-scale farmers, students, and organic farming enthusiasts, adapting to different crops and skill levels.
- With real-time monitoring, predictive analytics, and AI diagnostics, it reduces water wastage and supports sustainable crop yield optimization.

Objectives

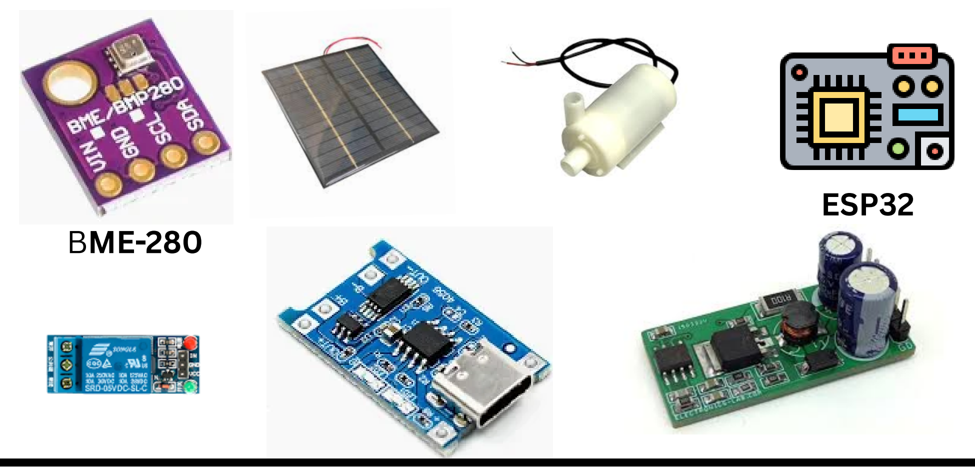
- To monitor soil moisture in real-time using IoT based sensors.
- To predict rainfall probability with a machine learning model using weather data, optimizing irrigation to conserve water.
- To provide crop-specific soil-water condition recommendations based on moisture data analysis, enhancing yield using a LLM.
- To diagnose crop pests/diseases via Likewise API analyzing farmer-uploaded photos, offering tailored treatment suggestions in-app.

Diagram



Technology Stack

Hardware used:

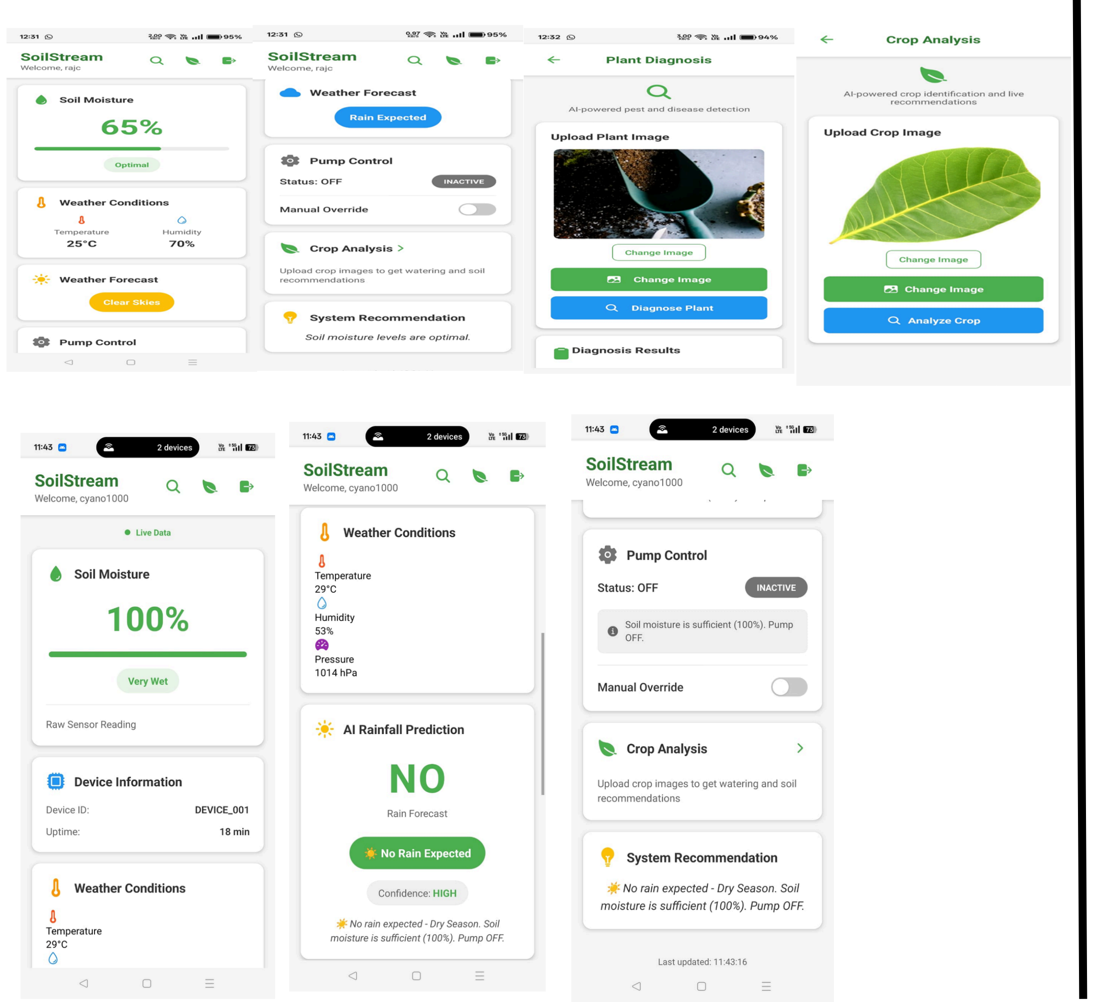


Software Used:

React Native

Firebase

USAGE



SDG's

RESULTS AND DISCUSSION

Comparison of Model Performance Metrics

Metrics	VGG16	ResNet50	EfficientNetB0
Accuracy	0.956	0.997	0.1601
Validation Accuracy	0.9404	0.9648	0.9976
Loss	0.2350	0.0139	7826.8145
Validation Loss	0.2206	0.1225	0.0406
Macro Avg. Precision	0.95	0.97	0.05
Macro Avg. Recall	0.95	0.96	0.11
Macro Avg. F1-Score	0.95	0.96	0.05
Weighted Avg. Precision	0.96	0.97	0.06
Weighted Avg. Recall	0.95	0.97	0.16
Weighted Avg. F1-Score	0.95	0.97	0.07

B. Rainfall Prediction Performance

TABLE II
Rainfall Occurrence Prediction Performance on Dataset-1 (Mumbai + Ratnagiri)

Algorithm	Accuracy	Precision	Recall	F1-Score
SVR	0.9286	0.9257	0.8954	0.9103
LightGBM	0.9232	0.9087	0.9007	0.9047
GRU	0.9230	0.9195	0.8873	0.9031

TABLE III
Rainfall Occurrence Prediction Performance on Dataset-2 (Mumbai + Ratnagiri + Thane + Pune)

Algorithm	Accuracy	Precision	Recall	F1-Score
SVR	0.9147	0.9310	0.8725	0.9008
LightGBM	0.9155	0.9232	0.8832	0.9027
GRU	0.9138	0.9166	0.8863	0.9012

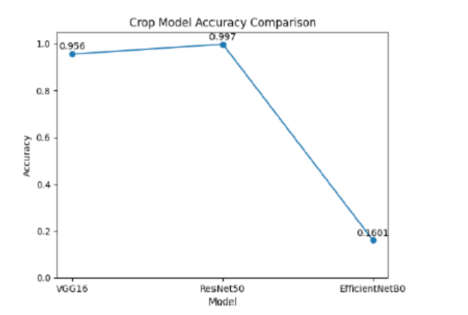


Fig. 2. Comparative accuracy performance for VGG16, ResNet50, and EfficientNetB0 for multi-class crop classification

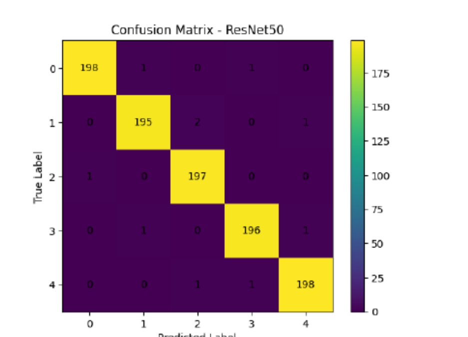


Fig. 3. Confusion matrix of the selected ResNet50 model showing class-wise crop classification performance.

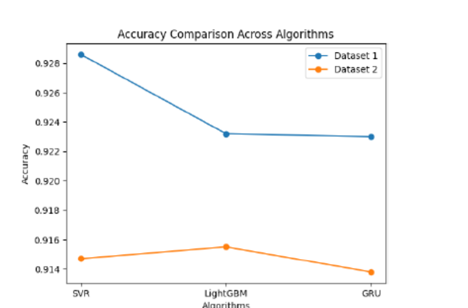


Fig. 4. Comparative rainfall occurrence prediction accuracy of SVR, Light-GBM. and GRU across Dataset–1 and Dataset–2.