OPTIMISING AGRICULTURAL PRACTISES IN ARID AND SEMI-ARID REGIONS USING REMOTE SENSING AND MACHINE LEARNING

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Introduction:

Agriculture in arid and semi-arid regions presents unique challenges, such as limited water availability, degraded soil conditions, and unpredictable climatic patterns. Traditional farming techniques often fall short in addressing these issues effectively. To ensure sustainable productivity, it is essential to adopt data-driven, location-specific agricultural strategies. This project aims to leverage remote sensing and machine learning to optimize agricultural practices by analyzing satellite imagery, ground-truth data, and geospatial indicators. The system identifies aridity levels, estimates soil moisture, and suggests actionable recommendations for farmers. Through mobile and web-based tools, the project delivers real-time decision support, customized crop planning, and irrigation management. The integration of cutting-edge technologies into traditional farming practices aligns with sustainable development goals and addresses pressing issues in climate-resilient agriculture.

Objectives:

- To detect and classify aridity levels in agricultural regions using remote sensing data.

- To estimate soil moisture content using satellite imagery and ground-truth validation.

- To build machine learning models that generate data-driven agricultural recommendations.
- To analyze land use and cropping patterns through geospatial classification techniques.
- To develop a mobile and web application for providing real-time decision support to farmers.
- To enhance sustainable agriculture through optimized crop planning and irrigation guidance.
- To ensure system scalability and adaptability across varied agro-climatic zones.

Methodology

The project leverages multi-source satellite datasets—MODIS (LST, albedo), Landsat-8 (land cover), Sentinel-1 (SAR-based soil moisture), Sentinel-2 (NDVI, EVI), and WorldView-2 (high-resolution validation)—ingested through Google Earth Engine. Ground-truth data including gravimetric soil moisture and crop yield is collected from field sites, with meteorological data aiding temporal normalization.

All imagery undergoes preprocessing: atmospheric correction (Sen2Cor), geometric rectification, and cloud masking. Indices such as NDVI, SAVI, MSI, and NDSI are computed and harmonized over time for consistent spatiotemporal analysis.

Features including SAR backscatter, spectral vegetation indices, terrain metrics (slope, aspect), and DEM layers are extracted. These are input to automated ML pipelines comprising Random Forest, XGBoost, CNNs, and SVMs for supervised prediction, and K-Means and SOMs for unsupervised classification of aridity zones.

Processed outputs are stored in a PostgreSQL/PostGIS geodatabase. A Flutter-based mobile app, connected via RESTful APIs, provides real-time soil and crop insights. A temporal report generation server delivers periodic recommendations. The system is validated using RMSE, R^2, and cross-validation, ensuring reliability and scalability.

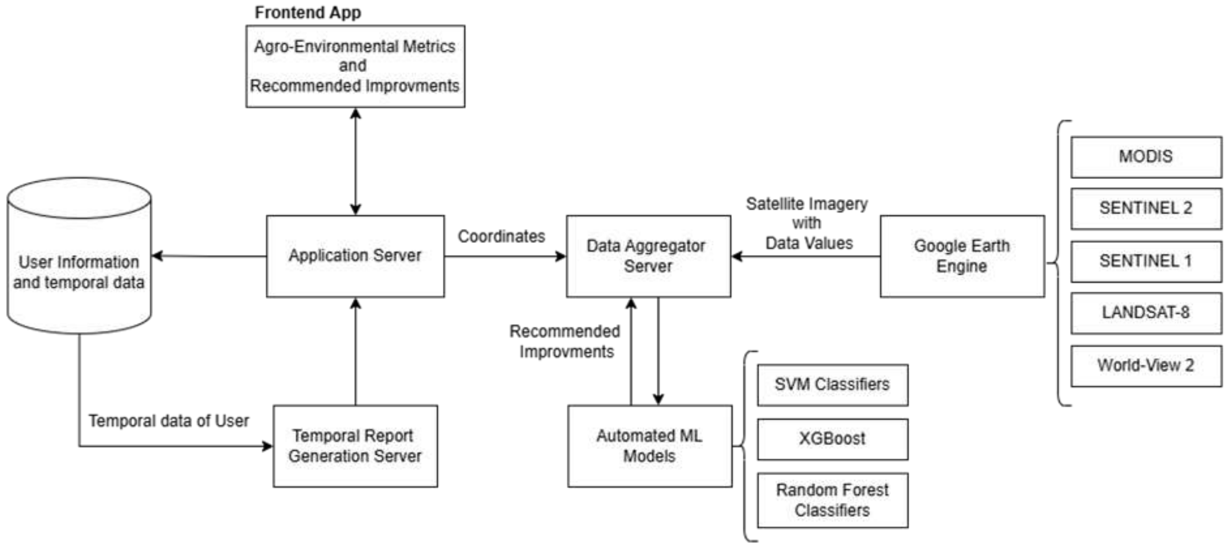

Figure 1: System architecture integrating satellite inputs, machine learning models, and user interface components.

Result and Conclusion:

The project demonstrates that remote sensing combined with machine learning can effectively analyze arid agricultural zones, estimate soil moisture, and support optimized farming decisions. Satellite datasets such as Sentinel-1 and Sentinel-2, when preprocessed and paired with ground-truth data, delivered high-accuracy predictions for soil moisture and vegetation health. Machine learning models like Random Forest and XGBoost achieved strong performance metrics, with low RMSE and high R^2 values.

The developed mobile application successfully provides users with real-time insights on aridity levels, land use patterns, and irrigation needs. The system's decision-support capabilities were validated through pilot testing, proving its relevance in aiding farmers with critical information for planning and resource optimization.

The classification of land use patterns through geospatial analysis was effective in identifying intercropping zones and fallow land, supporting better land management. These results reinforce the viability of AI-driven, satellite-based agriculture tools in resource-limited, climate-stressed environments.

Future Scope:

The project opens multiple avenues for future development in the domain of precision agriculture. One key extension involves incorporating land encroachment detection using temporal satellite imagery and classification techniques to monitor unauthorized changes in agricultural land use. This can help safeguard farmland and ensure better planning and compliance with sustainable agricultural practices.

The application can be further enhanced by integrating localized weather forecasting and adaptive crop recommendation systems based on seasonal variations. The system architecture can support multi-language interfaces, offline functionality, and region-specific datasets to increase usability among small and marginal farmers.

Advanced modules can be developed to predict pest outbreaks, nutrient deficiencies, and crop yields using deep learning models. Further research can explore hybrid models that combine remote sensing data with terrain and socio-economic indicators to improve the accuracy of aridity classification. Integration with government platforms and data-sharing APIs with agritech providers can drive industry-level adoption. Large-scale deployments across diverse agro-climatic zones will validate the system's scalability and support climate-resilient agricultural strategies.