Software Requirements Specification (SRS) Document

Project Name: FARMASSIST: A Virtual Assistant for Farmers

Introduction

FARMASSIST is a crop recommendation system designed to assist farmers in making informed decisions about which crops to cultivate based on various environmental and soil parameters. By utilizing machine learning algorithms, FARMASSIST predicts the most suitable crop for a given set of input parameters, helping farmers optimize their agricultural practices and maximize yields.

Purpose

The purpose of this document is to provide a comprehensive overview of the requirements for the development of FARMASSIST. It outlines the system's functionalities, constraints, and interfaces to ensure a clear understanding of the project scope for all stakeholders involved.

Scope

FARMASSIST aims to be a user-friendly virtual assistant accessible via web or mobile platforms. It will take seven input parameters related to environmental and soil conditions from the user and provide a recommended crop based on machine learning models trained on historical agricultural data. The system will prioritize accuracy, efficiency, and scalability to accommodate a wide range of users and geographical locations.

Functional Requirements

1 Input Parameters

Soil Type: The user shall select the type of soil from predefined options (e.g., sandy, loamy, clayey).

pH Level: The user shall input the pH level of the soil (numeric value).

Temperature: The user shall input the average temperature of the region (numeric value in Celsius).
Humidity: The user shall input the average humidity level of the region (numeric value in percentage).
Rainfall: The user shall input the average annual rainfall of the region (numeric value in millimeters).
Crop Rotation: The user shall specify whether crop rotation is practiced in the farmland (yes/no).
Previous Crop: If crop rotation is practiced, the user shall specify the previous crop grown.

2 Output

Recommended Crop: The system shall output the recommended crop based on the input parameters.

3 Machine Learning Model

Training Data: The system shall utilize historical agricultural data for training the machine learning model.
Algorithm: The system shall employ a suitable machine learning algorithm for crop prediction, such as decision trees, random forests, or support vector machines.
Accuracy: The system shall strive for high accuracy in crop recommendations based on the trained model.

Non-Functional Requirements

1 Performance

Response Time: The system shall respond to user inputs within seconds.
Scalability: The system shall be capable of handling a large volume of users simultaneously.

2 Usability

User Interface: The system shall feature an intuitive and user-friendly interface for inputting parameters and viewing recommendations.
Accessibility: The system shall be accessible via web browsers and mobile applications.

3 Reliability

Availability: The system shall be available for use 24/7 with minimal downtime for maintenance.
Error Handling: The system shall provide meaningful error messages in case of invalid input or technical issues.

4 Security

Data Privacy: The system shall adhere to data privacy regulations and ensure the confidentiality of user information.
Authentication: The system may implement user authentication mechanisms to secure access to sensitive features or data.

Constraints

Data Availability: The accuracy of crop recommendations depends on the availability and quality of historical agricultural data.
Environmental Variability: The system's predictions may vary based on changes in environmental factors not accounted for in the input parameters.

References

[1] Katarya, R., Raturi, A., Mehndiratta, A., & Thapper, A. (2020). *Impact of Machine Learning Techniques in Precision Agriculture*. https://doi.org/10.1109/icetce48199.2020.9091741

[2] Liakos, K. G., Busato, P., Moshou, D., Pearson, S., & Bochtis, D. (2018). Machine Learning in Agriculture: A Review. *Sensors*, *18*(8), 2674. https://doi.org/10.3390/s18082674

[3] Balkrishnan, N., & Muthukumarasamy, G. (2022). Crop production Ensemble Machine Learning model for prediction.
International Journal of Computer Science and Software Engineering (IJCSSE)

[4] Jia, Z. (2009). *An Expert System Based on Spatial Data Mining Used Decision Tree for Agriculture Land Grading*. https://doi.org/10.1109/icicta.2009.751

[5] Khan, M., Islam, Z., & Hafeez, M. (2012). Evaluating the performance of several data mining methods for predicting irrigation water requirements. In *Australasian Data Mining Conference* (pp. 199–207). http://crpit.com/confpapers/CRPITV134Khan.pdf

[6] Dhanya, C. T., & Kumar, D. (2009). Data mining for evolution of association rules for droughts and floods in India using climate inputs. *Journal of Geophysical Research*, *114*(D2). https://doi.org/10.1029/2008jd010485

[7] Rale, N., Solanki, R., Bein, D., Andro-Vasko, J., & Bein, W. W. (2019). *Prediction of Crop Cultivation*. https://doi.org/10.1109/ccwc.2019.8666445

[8] Ramesh, D., & Vardhan, B. V. (2015). ANALYSIS OF CROP YIELD PREDICTION USING DATA MINING TECHNIQUES. *International Journal of Research in Engineering and Technology*, *04*(01), 470–473. https://doi.org/10.15623/ijret.2015.0401071

[9] Mishra, S., Mishra, D., & Santra, G. H. (2016). Applications of Machine Learning Techniques in Agricultural Crop Production: A Review Paper. *Indian Journal of Science and Technology*, *9*(38). https://doi.org/10.17485/ijst/2016/v9i38/95032

[10] Baisali, G. (2016) A Study to Determine Yield for Crop Insurance using Precision Agriculture on an Aerial Platform. Symbiosis Institute of Geoinformatics. Symbiosis International University 5th & 6th Floor, Atur Centre, Gokhale Cross Road, Model Colony, Pune – 411016.

[11] Jeong, J. H., Resop, J. P., Mueller, N. D., Fleisher, D. H., Yun, K., Butler, E. E., Timlin, D., Shim, K., Gerber, J. S., Reddy, V. R., & Kim, S. (2016). Random Forests for Global and Regional Crop Yield Predictions. *PLOS ONE*, *11*(6), e0156571. https://doi.org/10.1371/journal.pone.0156571