Abstract

Agriculture is facing increasing challenges due to global climate shift, water scarcity, and the global need for sustainable food production. Traditional farming methods are often unable to respond efficiently to these dynamic environmental conditions. The thesis presents an integrated system that combines Internet of Things (IoT), Hybrid Machine Learning (HML), and Explainable Artificial Intelligence (XAI) to enhance decision-making in every stage of modern agriculture. The research moves from understanding environmental conditions to building intelligent, sustainable, and transparent systems that assist agriculturalists in making evidence-based decisions.

The work begins with the development of an intelligent rainfall prediction model, recognizing that understanding the environment is the foundation of effective farming. A novel Ant Colony Optimization-based Neural Network (ACO-NN) is presented to forecast daily rainfall in Alipurduar, West Bengal. By integrating key weather parameters and optimizing the neural architecture through ACO, the method achieves high prediction accuracy and significantly reduces errors. Accurate rainfall forecasting enables farmers to plan irrigation schedules and crop management strategies well in advance, marking a major step toward precision agriculture.

Building on this environmental understanding, the work presents an intelligent irrigation system that combines IoT-based sensors with HML models optimized using a Genetic Algorithm (GA). The system predicts the precise water requirements of coriander plants across different growth stages using solar radiation data captured by the BH1750 sensor to estimate evapotranspiration (EV_{T0}). The best-performing hybrid model achieves an accuracy of 0.98%, ensuring efficient irrigation and water conservation. A mobile-based monitoring system further allows farmers to control irrigation remotely, reducing both water wastage and manual labor. The work then focuses on improving soil health through soil fertility classification. A hybrid ACO-XGBoost model is designed to classify soil fertility based on micro and macronutrients, achieving 98% accuracy. The integration of XAI techniques helps to explain the model's decisions, allowing farmers to understand which nutrients influence soil fertility the most. This interpretability turns complex soil data into practical guidance for fertilizer management and soil improvement.

To promote environmentally responsible farming, an eco-friendly hybrid machine learning (EHML) system is developed for sustainable crop and fertilizer recommendation. Models like CatBoost and XGBoost are optimized with nature-inspired algorithms, achieving accuracies above 98%. XAI methods reveal the reasoning behind each recommendation, while environmental indicators such as CO_2 emissions and energy use are analyzed to promote green agricultural practices. A web application is also built to deliver real-time, interpretable crop and fertilizer recommendations to farmers.

Finally, an Explainable AI framework for a crop yield forecasting system is proposed to build transparency and trust in AI-driven decisions. The framework combines global, local, and counterfactual explanations to show how various factors affect yield. Random Forest and AdaBoost models achieve the best results, while a new XAI-based feature selection method highlights the most influential factors. This framework enables farmers to understand and trust AI predictions.
