Applying Machine Learning to Agriculture : Review for Challenges and Outcome

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***Abstract*—Sri Lanka is an agricultural country. historically, agriculture has been the most important sector of the Sri Lankan economy. Nowadays agriculture affects by various factors such as lack of manpower, inefficient resource use, low crop yields, vulnerability to climate change, etc. To help the farmers from the above factors and increase agriculture production, recently many machine learning techniques are utilized in the agricultural field. Agriculture Prompt Engineering, an innovative approach integrating AI offers a powerful solution to these issues. By adopting precision farming techniques and using AI models to guide data collection and decision making, Sri Lankan farmers can optimize their use of resources, predict crop yields and adapt to changing climate conditions. The main goal of this work is to provide detailed information about various machine-learning techniques that can be used in agriculture recently to improve agricultural production.**

Keywords – Machine Learning, Deep Learning, Agriculture, Artificial Inteligence, Data-Driven Decision Making

1. INTRODUCTION

Sri Lanka's agricultural sector the backbone of its economy. Continues to struggle with numerous issues, including outdated practices, climate vulnerability and inefficient resource management. Despite agriculture employing a significant portion of the population, productivity remains low and the sector's contribution to the GDP is limited[1].

The global shift towards digital transformation presents an opportunity to modernize Sri Lankan agriculture. Agriculture Prompt Engineering leverages the power of artificial intelligence (AI) and machine learning (ML) to provide real-time insights, optimize resource use and tackle key agricultural challenges like irrigation management, crop disease prediction and supply chain optimization. Implementing these advanced technologies can elevate Sri Lanka's agricultural productivity while ensuring sustainability and climate resilience.

The agricultural sector, which occupies about 1.35 million hectares, or more than 30% of the nation's land area, is essential to both economic stability and food security[2]. Small-scale farmers who cultivate less than two hectares each oversee a sizable portion of this agricultural land and together produce almost 80% of the nation's annual crop production[3].Due to urbanization, land availability for agriculture will decrease.

However, traditional farming methods are often challenged by climate variability, lack of timely market Information, crop disease prediction, manpower and inefficiencies in the supply chain.

It is becoming more and more important to incorporate cutting-edge technologies into conventional farming methods as the demands for sustainable practices and food security increase.

It is the correct time when automation through artificial intelligence can enter the field of agriculture. The machine learning branch of Artificial Intelligence gives the skill to a machine to learn from experience. Its algorithm does not depend on a predefined model rather they learn from a dataset. Machine learning can take better decisions without involving humans to solve real-world problems.

By providing data-driven insights that increase farming productivity and financial stability, machine learning technology has the potential to revolutionize the industry. However, a number of obstacles frequently stand in the way of the adoption of these technologies in agriculture, such as the difficulty of implementing the model and the lack of pertinent data. By creating a full suite of predictive models to assist farmers in choosing crops and forecasting agricultural market prices, this study tackles these issues.

This research discusses the experimental previous years' papers to explore the role of machine learning in agriculture and other challenges, which explain how machine learning can be used in agriculture to address the problems and challenges in this sector.

2. LITERAURE REVIEW

An Overview on Machine Learning

Typically,ML methodologies involves a learning process with the objective to learn from "experience" (training data) to perform a task. The performance of the ML model in a specific task is measured by a performance metric that is improved with experience over time. To calculate the performance of ML models and algorithms, various statistical and mathematical models are used. After the end of the learning process, metric that is improved with experience over time. To calculate the performance of ML models and algorithms, various statistical and mathematical models are used. After the end of the learning process, the trained model can be used to classify, predict, or cluster new examples (testing data) using the experience obtained during the training [4].

researchers applying machine learning in different fields of agriculture. The machine learning algorithms are mainly applied in the following areas of agriculture such as plant monitoring, smart agriculture, prediction (or) detection in the agricultural process, animal monitoring. The brief details about these applications are given below.

2.1 Smart Agriculture with Machine Learning

Climate variability, market volatility and supply chain inefficiencies are some of the major issues facing Sri Lanka's agriculture industry. These issues make it difficult for small-scale farmers to make well-informed decisions regarding crop selection and price trends. In order to solve these problems, this study suggests a smart agriculture system that integrates machine learning (ML) models into an intuitive web platform. The models include the Random Forest Classifier for crop recommendations and the CatBoost Regressor for price forecasting.
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2.2 Machine Learning in Agricultural Prediction/Detection

This section comprehensively surveys machine learning (ML) applications in agriculture for disease prediction, crop quality assessment and environmental monitoring. ML technique such as extreme learning machines, KNN, ANN, SVM and deep learning integrated with technologies like acoustic signal processing, hyperspectral imaging and computer vision. For instance, ML models achieved high accuracy in detecting wheat kernel damage (via acoustic signals) [6], pepper fusarium disease (using classifiers like KNN and ANN) and mango maturity. Deep learning approaches, such as CNNs, excelled in plant disease detection using leaf images [7], while ensemble methods (e.g., Random Forests) optimized predictions for crop stress factors like physiological temperatures in livestock . However, the section lacks critical analysis comparing algorithm efficacy across studies, and some applications feel tangential to the core focus on plant-related challenges. The writing occasionally suffers from grammatical inconsistencies (e.g. "applied with computer vision technology in order to classify rapeseed") and transitions between topics (disease detection, resource management) could be smoother. A notable trend is the integration of ML with auxiliary technologies (e.g. image processing for nutrient deficiency detection, underscoring its interdisciplinary potential.

To strengthen the review, a concluding synthesis of key findings (e.g. the dominance of deep learning in image-based tasks) and future directions (e.g. scalability of hybrid models) would enhance coherence. Overall, the content provides valuable insights into ML's transformative role in agriculture but requires structural refinement and deeper comparative analysis to maximize impact.

2.3 Machine Learning in Plant Monitoring

Monitoring plants is one of the basic function of farming. Various machine learning techniques are applied to monitor plants. applications of machine learning (ML) in agricultural plant monitoring, spanning growth analysis, pest detection, ripeness estimation, and cultivar classification. Studies like [8] demonstrate effective integration of ML with technologies such as computer vision and drones e.g., using PCA/SVM for tomato ripeness staging and deep learning with NDVI sensors for large-scale lettuce phenotyping.

However, the section suffers from structural disorganization, jumping between unrelated applications (e.g., hydrogen production in which seems tangential) without thematic grouping. While methodologies like CNNs for sugar beet classification [9] and sparse linear adaptive structures for plant factories [6] highlight technical diversity, key details are often missing such as performance metrics.

All things showcases interdisciplinary approaches and Balances traditional ML (SVM, PCA) and modern deep learning (CNNs, DSELMs), reflecting evolving trends.

3. Discussion and Comparison

This study assesses various machine learning (ML) applications in agriculture with an emphasis on how well they address the issues facing Sri Lanka and other agricultural countries. The effectiveness of these methods, a comparison of their advantages and disadvantages, and an examination of their applicability to Sri Lankan farmers are covered below.

3.1 Comparative Analysis of ML Techniques

A) Price Forecasting & Crop Recommendations
In managing non-linear relationships and feature interactions, the suggested CatBoost Regressor (RMSE: 42.4) and Random Forest Classifier (accuracy: 99.7%) perform better than conventional models like SARIMAX. For Sri Lanka's inconsistent datasets, CatBoost's gradient-boosting framework effectively handles missing values and categorical data. Similar to this, Random Forest's ensemble method minimizes overfitting, which makes it reliable for crop recommendations even in the face of sparse local data. On the other hand, less complex models such as linear regression or decision trees are unable to adequately represent Sri Lanka's erratic weather and market trends.

B) Disease Detection & Quality Assessment
Deep learning models like CNNs can extract hierarchical features, they perform exceptionally well in image-based tasks (like leaf disease detection [7]), with controlled studies showing>90% accuracy. However, Sri Lanka's resource-constrained environments face difficulties due to their reliance on sizable labeled datasets and computational resources. Although less accurate (about 80–85% accuracy), traditional machine learning techniques like SVM and KNN are practical for small farms due to their quicker implementation and cheaper costs.

C) Plant Monitoring & Yield Prediction
Hybrid methods, like drone-based NDVI sensors with CNNs [9] or PCA-SVM for tomato ripeness staging [8], show great precision but demand sophisticated infrastructure. Because they rely less on high-resolution sensors, simpler methods like acoustic signal processing for crop damage detection [6] or Random Forest-based pest hotspot prediction might be more practical for Sri Lanka.

3.2 Practical Challenges in Sri Lankan Context

A) Data Scarcity & Quality
Machine learning models like CNNs and CatBoost rely on large datasets, but Sri Lanka's dispersed agricultural data, poor digitization, and regional gaps hinder generalizability.

B) Infrastructure & Accessibility
Smallholder farmers face high costs and technical complexity in deep learning and hyperspectral imaging, while IoT sensors and mobile-friendly tools offer more scalable solutions.

C) Interdisciplinary Integration
Successful examples highlight the importance of integrating machine learning with low-cost technologies like drone-based phenotyping, while peripheral uses like hydrogen production distract from essential agricultural needs.

5. Conclusion

This study highlights how machine learning can be used to address Sri Lanka's agricultural issues, ranging from price volatility to climate resilience. The suggested smart agriculture system, which combines Random Forest and CatBoost models, shows how machine learning (ML) can improve smallholder farmers' decision-making by providing precise crop recommendations (99.7% accuracy) and price forecasts (RMSE: 42.4). Still, a significant drawback is the dependence on expensive technologies and non-local datasets.

Key findings stress the need for context-appropriate solutions while highlighting the superiority of deep learning and ensemble approaches in complex tasks. Prioritizing low-resource, scalable models and encouraging interdisciplinary partnerships (like AI with IoT) will be crucial for Sri Lanka. To guarantee fair access, future research should concentrate on farmer training, mobile technology integration, and localized data collection. This research lays the groundwork for sustainable, data-driven agriculture in Sri Lanka and other agricultural countries by bridging the gap between technological innovation and practical realities. This aligns with global goals of climate adaptation and food security.

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