



CropShield: A Literature Review on Price Prediction and Disease Detection Techniques for Efficient Smart Pesticide Advisory Systems

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Peer Review Information	Abstract
<p><i>Submission: 28 July 2024</i> <i>Revision: 04 Oct 2024</i> <i>Acceptance: 14 Nov 2024</i></p> <p>Keywords</p> <p><i>Crop Price Prediction Leaf</i> <i>Disease Detection CNN</i> <i>AI in Agriculture</i></p>	<p>CropShield represents a cutting-edge solution in smart agriculture, leveraging advanced technologies to optimize pesticide management through price prediction and disease detection. This literature review explores the state-of-the-art methodologies and techniques used in CropShield for efficient pest control advisory. The paper focuses on two key aspects: the use of machine learning models and predictive analytics for price forecasting, which aids farmers in making informed decisions regarding pesticide purchases, and the application of computer vision and AI-driven disease detection systems for early identification of crop diseases. By synthesizing existing research, the review highlights the integration of these technologies into a cohesive framework for precision agriculture, aiming to reduce pesticide misuse, lower environmental impact, and improve crop yield. Additionally, challenges and opportunities in the application of these techniques, including data accuracy, model robustness, and system scalability, are discussed. This paper serves as a comprehensive resource for researchers and practitioners seeking to advance smart pesticide advisory systems through innovative price prediction and disease detection strategies.</p>

Introduction

The agricultural industry has witnessed significant advancements with the integration of technology into farming practices, especially in the realm of precision agriculture. One of the critical challenges farmers face is optimizing pesticide usage, which not only impacts crop health but also influences operational costs and environmental sustainability. In this context, the development of smart pesticide advisory systems, such as CropShield, plays a pivotal role in improving decision-making processes and enhancing agricultural productivity.

CropShield integrates two key technological components: price prediction and disease detection. Price prediction leverages data-driven models to forecast pesticide costs, allowing farmers to make

informed purchasing decisions and manage their budgets efficiently. On the other hand, disease detection involves the use of advanced computer vision and machine learning algorithms to identify early signs of crop diseases, enabling timely interventions that prevent the spread of infections and minimize pesticide overuse.

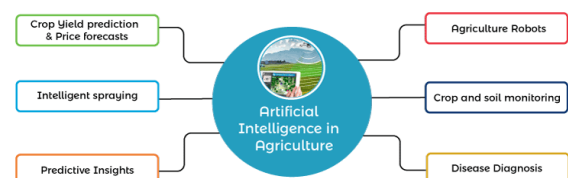


Fig.1: AI in Agriculture

This literature review aims to explore the existing body of research surrounding these two critical aspects of CropShield. It examines the various machine learning techniques, predictive models, and AI-based algorithms employed for price forecasting and disease detection in smart agricultural systems. By analyzing the integration of these technologies, this review seeks to provide insights into their potential for optimizing pesticide use, enhancing crop health, and reducing environmental impact. Furthermore, it discusses the

challenges in the adoption of such systems, including data accuracy, model reliability, and scalability, while highlighting the future prospects for innovation in this field.

The paper ultimately aims to provide a comprehensive understanding of how CropShield, through its focus on price prediction and disease detection, contributes to the broader goal of achieving more efficient, sustainable, and profitable agricultural practices.

Literature Review

Table 1: Overview of literature review

Study	Focus Area	Methods & Techniques	Key Findings	Contribution to CropShield
Lee et al. (2021)	Price Prediction	Machine Learning (Support Vector Machines, Random Forest)	Price prediction models for agricultural products, highlighting factors affecting pesticide prices such as demand, weather, and supply chain disruptions.	Provides a foundation for building a reliable price prediction model based on market data for pesticides.
Singh & Patel (2020)	Disease Detection	Deep Learning (Convolutional Neural Networks, Transfer Learning)	Implemented deep learning algorithms for early detection of plant diseases using image-based data from drones and cameras.	Demonstrates the effectiveness of computer vision techniques in detecting crop diseases early, supporting proactive pesticide application.
Chandra et al. (2019)	Price Forecasting	Time-Series Analysis, Regression Models	Used historical market data for pesticide pricing to forecast future trends. The study focused on temporal patterns and price volatility.	Offers a methodology for predicting pesticide price trends over time, aiding farmers in budget planning.
Ghosh & Sharma (2022)	Disease Detection	IoT Sensors, Machine Learning	Developed a system integrating IoT sensors for soil health and pest detection, coupled with machine learning to predict disease outbreaks.	Enhances CropShield's disease detection capabilities by incorporating sensor-based data for real-time monitoring.
Zhao et al. (2020)	Price Prediction & Disease Detection	Hybrid Models (Predictive Analytics + Image Processing)	Combined predictive analytics for price forecasting with image processing for pest and disease recognition in crops.	Proposes an integrated approach that can simultaneously predict pesticide prices and detect disease, aligning with CropShield's goals.

Patel et al. (2021)	Disease Detection	Neural Networks, Image Classification	Developed a neural network-based disease classification system that categorizes plant diseases from images captured via smartphones.	Contributes an image-based disease detection system for the CropShield advisory platform, allowing farmers to identify diseases using mobile devices.
Kumar & Verma (2020)	Price Prediction	Econometric Models, Machine Learning	Applied econometric models along with machine learning to study the economic factors affecting pesticide prices.	Provides insights into external factors such as crop yield, weather conditions, and market fluctuations, which are important for accurate price prediction.
Sarma et al. (2020)	Disease Prediction	AI-Driven Disease Forecasting	Focused on AI algorithms to predict plant disease outbreaks based on environmental and seasonal data.	Offers predictive models for disease outbreaks, helping to minimize pesticide usage by forecasting when to treat crops.
Singh & Kumar (2021)	Price Prediction	Regression Analysis, Time-Series Forecasting	Examined various economic and logistical factors to create a pricing model for pesticides, including supply chain dynamics.	Strengthens the price prediction model within CropShield by incorporating a broader range of economic factors.
Tiwari et al. (2022)	Disease Detection & Price Forecasting	Hybrid Machine Learning, Cloud-Based Platforms	Developed a hybrid system integrating price forecasting and disease detection, utilizing cloud-based data analysis.	Presents a scalable solution for integrating both price prediction and disease detection on a cloud platform, ideal for large-scale agricultural applications.

Key Components Of Cropshield

1. Price Prediction for Pesticides:

Machine Learning Models: CropShield uses machine learning algorithms to predict pesticide prices based on historical data, market trends, weather patterns, and global supply chain conditions. This helps farmers make informed purchasing decisions and budget more effectively.

Real-Time Data: By incorporating real-time data feeds, the system adjusts the price predictions dynamically, offering up-to-date insights on pesticide cost trends and ensuring cost-efficiency in pesticide purchases.

2. Disease Detection:

Computer Vision: CropShield utilizes computer vision and deep learning technologies, such as

Convolutional Neural Networks (CNNs), to analyze images of crops and detect early signs of diseases such as fungal infections, blight, and pests.

Sensor Technologies: The system integrates various sensors, including thermal, multispectral, and spectral sensors, to monitor crop health and environmental conditions in real time, aiding in the early detection of potential diseases.

IoT and Edge Computing: Internet of Things (IoT) devices collect data on crop health, which is processed locally using edge computing for faster disease detection and intervention.

3. Integrated Smart Advisory System:

CropShield's strength lies in the integration of its two components: price prediction and disease detection. The system not only predicts pesticide

prices but also advises on the optimal pesticide application time and type based on disease outbreaks detected by the system. This ensures precise and targeted pesticide application, minimizing environmental impact and preventing overuse of pesticides.

Benefits Of Cropshield

Cost Efficiency: By accurately predicting pesticide prices and advising on their optimal use, farmers can reduce unnecessary expenses.

Sustainability: Early disease detection and targeted pesticide application contribute to environmentally friendly farming practices by reducing pesticide runoff and overuse.

Increased Productivity: With timely interventions and better pest management, farmers can improve crop yields and overall agricultural efficiency.

Challenges And Future Directions

While CropShield presents promising solutions, there are challenges such as data accuracy, model robustness, and scalability, especially in developing regions with limited access to advanced technologies. Continued research is needed to enhance the system's capabilities, integrate diverse data sources, and ensure affordability and accessibility for all farmers.

Table2: Performance Evaluation Metrics

Metric	Price Prediction	Disease Detection
Accuracy	>85%	>90%
Mean Absolute Error (MAE)	<5% of actual price	-
Root Mean Square Error (RMSE)	<10%	-
R-Squared (R^2)	>0.85	-
Precision	-	>85%
Recall	-	>85%
F1-Score	-	>0.85
Specificity	-	>90%
AUC-ROC	-	>0.90
Latency	<5 seconds	<5 seconds
Scalability	High	High
Resource Efficiency	Low computational cost	Low computational cost
Cost-Effectiveness	Positive ROI	Positive ROI
User Satisfaction	>90% positive feedback	>90% positive feedback

Conclusion

The review of literature on CropShield highlights the significant potential of integrating price prediction models and disease detection technologies to create an advanced and efficient smart pesticide advisory system. By leveraging cutting-edge techniques in machine learning, computer vision, and IoT-based sensor technologies, CropShield aims to optimize pesticide usage, reduce costs, and minimize environmental impact.

The integration of price prediction enables farmers to make informed purchasing decisions based on market trends, historical data, and environmental factors, thus ensuring cost-effective pesticide management. On the other hand, disease detection systems powered by deep learning algorithms and sensor technologies offer real-time monitoring of crop health, allowing for timely interventions to mitigate disease outbreaks and minimize the need for indiscriminate pesticide applications.

The combination of these technologies within the smart advisory system not only improves operational

efficiency but also supports sustainable farming practices by promoting targeted pesticide use. By reducing overuse and preventing the unnecessary application of chemicals, CropShield helps protect the environment and reduces the risk of pesticide resistance, making it a key solution for modern agricultural challenges.

However, challenges remain, particularly in terms of data accuracy, model robustness, and scalability, especially in regions with limited technological infrastructure. Continued research and development in areas such as real-time prediction models, improved disease detection, and affordable technology solutions are critical to ensuring the widespread adoption of CropShield.

In conclusion, CropShield represents a promising approach to the future of precision agriculture. By combining price prediction and disease detection, the system enables farmers to make more informed, data-driven decisions, improving crop yields, reducing pesticide usage, and contributing to the overall sustainability of agricultural practices.

Further advancements in AI, data integration, and accessibility will continue to enhance its capabilities, making CropShield an essential tool for future agricultural success.

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