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Abstract

Predictive modeling for crop yield estimation has emerged as a crucial tool for enhancing agricultural productivity and ensuring food security, especially in the face of rapidly changing climatic conditions. This chapter explores the role of Artificial Intelligence (AI) in improving crop yield forecasts by integrating diverse data sources such as weather patterns, soil health, remote sensing data, and crop-specific parameters. The application of machine learning algorithms, including artificial neural networks and support vector machines, enables the modeling of complex, non-linear relationships between environmental variables and crop growth. The chapter further discusses the integration of multi-source data fusion techniques, which allow for the combination of high-resolution spatial and temporal datasets to generate accurate, real-time yield predictions. Challenges related to data availability, quality, and the legal and ethical considerations in data sharing are also addressed, highlighting the need for robust data governance frameworks. By leveraging cutting-edge AI techniques, this work provides a comprehensive overview of the current state of crop yield prediction and offers insights into future research directions. The chapter emphasizes the importance of optimizing data resolution, improving model generalization, and ensuring equitable access to agricultural data for sustainable farming practices worldwide.

Keywords: crop yield prediction, artificial intelligence, machine learning, multi-source data fusion, data governance, climate variability.

Introduction

The accurate prediction of crop yields is an essential aspect of modern agriculture, playing a critical role in ensuring food security, managing resources efficiently, and supporting sustainable farming practices [1]. As climate conditions become increasingly unpredictable, traditional methods of yield estimation, which often rely on historical data and expert judgment, are no longer sufficient to meet the growing demands of global food production [2]. The rapid advancements in data collection technologies, including remote sensing, soil sensors, and weather forecasting, have created an opportunity to leverage Artificial Intelligence (AI) to improve the accuracy and reliability of crop yield predictions [3]. AI offers the potential to process vast amounts of data from multiple sources and uncover complex, non-linear relationships that were previously difficult to identify with conventional methods [4]. By combining environmental data with machine learning models, predictive tools can be developed that provide real-time, actionable insights for farmers, policymakers, and agricultural stakeholders [5].

The integration of machine learning (ML) and deep learning (DL) models has become a central approach to crop yield forecasting [6]. These algorithms are particularly suited to handle the large and complex datasets generated by modern agricultural technologies [7]. For instance, artificial neural networks (ANNs) and support vector machines (SVMs) can analyze data from a variety of sources, such as climate conditions, soil health, crop growth stages, and remote sensing imagery, to identify patterns and predict future crop yields [8]. Unlike traditional linear models, which often oversimplify the relationships between environmental variables, AI models can capture intricate, non-linear interactions, offering a more accurate representation of the complex systems that influence crop performance. Machine learning techniques also have the advantage of continuous learning, which allows them to adapt over time as more data is collected, improving the precision of predictions as new environmental conditions arise [9, 10].

One of the key advantages of AI in crop yield estimation is its ability to integrate multi-source data fusion [11]. By combining datasets from diverse sources such as satellite imagery, weather forecasts, soil moisture sensors, and historical yield records AI models can provide a more holistic view of the factors influencing crop growth. Remote sensing technologies, such as satellite and drone imagery, offer valuable spatial data on vegetation health, while IoT-based sensors provide real-time insights into soil conditions and microclimates [12]. The fusion of these datasets enables predictive models to consider a wide range of variables simultaneously, resulting in more accurate and robust yield forecasts [13]. Moreover, the integration of temporal data, which tracks changes over time, helps to account for seasonal variations and fluctuations in crop growth, further improving the predictive capabilities of AI-driven models [14, 15].