 Review Article

FOOD SCIENCE AND AGRICULTURAL TECHNOLOGY

Digital Technology Application For Advanced Crop Yield Forecasting System

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Abstract

The adoption of digital technology has the potential to bring about a significant transformation in food production around the globe. Predicting crop yields is a difficult task in precision agriculture, and numerous models have been suggested and this case study review some of the technologies for crop yield forecasting, the strength, drawback and future improvement.

KEYWORDS: Crop Yield, Digitalization, Digital Technology, Forecasting Technology

Introduction

The global agriculture landscape has been significantly shaped by the growing need to meet the rising need for agri-food products over the years. Moreover, alterations in human lifestyles, coupled with the growth of the human population and urbanisation, have directly influenced the production and consumption of agri-food products (Abiri et al., 2023). The economic significance of strategic plants and the limited availability of agricultural resources have motivated plant producers and agricultural researchers to explore novel approaches to address the food crisis. So far, the agri-food sectors have incorporated contemporary technology and effective tactics (Scholz et al., 2018; Abiri et al., 2023). Nevertheless, investigations suggest locating and enhancing the existing agricultural and food instruments to address hunger and bridge the gap between demand

and supply by enhancing production efficiency. The adoption of digital technology has the potential to bring about a significant transformation in food production around the globe, as stated by Scholz et al. (2018) and Abiri et al. (2023). Digital Agriculture (DA) refers to applying advanced tools, data monitoring, analytics, and data-driven solutions in agriculture. The purpose is to enhance and optimise farming systems, improve crop quality and yield, minimise waste, and effectively manage pest and disease pressure (Scholz et al., 2018). Nyeki and Nemenyi (2022) assert that forecasting crop yields is a highly formidable undertaking in agriculture. It has a crucial function in global, regional, and local decision-making. Crop yield can be predicted using soil, climatic, environmental, and crop factors. Various decision support algorithms are employed to extract crucial crop characteristics for prediction. Precision agriculture encompasses sensing technology, management information systems, variable rate technologies, and strategies to address variability within and between cropping systems (Nyeki & Nemenyi, 2022). This case study report examines digitisation and its tools as a technology/system for predicting crop yields in agri-food businesses.

Technology for Predicting Crop Yields

Predicting crop yields is a difficult task in precision agriculture, and numerous models have been suggested and verified thus far (van Klompenburg et al., 2020; Bharatiya et al., 2023). Many datasets are necessary to address this issue as crop production is influenced by climate, weather, soil composition, fertiliser application, and seed type (Xu et al., 2019). This suggests that predicting crop yield is complex, including multiple intricate stages. Currently, crop yield forecasting models can reasonably estimate the actual yield. However, there is still a desire for improved performance in predicting yields (Filippi et al., 2019; van Klompenburg et al., 2020).

The significance of crop output forecasting is escalating as concerns around food security continue to rise. Preliminary forecasts of agricultural yield, which anticipate the supply of food for the growing global population, have the potential to mitigate famine significantly (Breure et al., 2022). Increasing food production is a potential solution to the pressing problem of ending world hunger, which is one of the most significant challenges of our time. According to the World Health Organisation, over 820 million individuals worldwide still do not have sufficient access to food despite some recent advancements (Holzworth et al., 2015; Bharatiya et al., 2023). The UN's Sustainable Development Goals for 2030 aim to address hunger, ensure food security, and promote sustainable agriculture (Tsani et al., 2020; Bharatiya et al., 2023). Forecasts of crop output might offer crucial information for formulating a feasible strategy to achieve the objective of eradicating hunger (You et al., 2017; Wang et al., 2018; Bharatiya et al., 2023). Forecasting crop production is a crucial responsibility for decision-makers at national and regional levels, such as the European Union, to make prompt and informed decisions (van Klompenburg et al., 2020). A precise crop yield prediction model can assist farmers in determining which crops to cultivate and the optimal timing for cultivation.

Emerging technologies and digital infrastructures, including robotics, remote sensing technologies, uncrewed aerial vehicles, artificial intelligence, and big data analytics, are facilitating the implementation of innovative farming practices worldwide, resulting in increased productivity levels (Boakye and Babatunde 2021; Boakye et al. 2021; Boakye, 2023). Crop yield is a primary metric for quantifying the productivity of agriculture. The assessment of crop production is vital to comprehend the effectiveness of novel agricultural approaches implemented in farming practices (Boakye, 2023). Various methodologies exist for predicting agricultural yields.

Kamath et al. (2022) asserted that crop production forecasting is an ideal application for data mining techniques due to the substantial volume of data involved. This research offers a rapid assessment of agricultural yield forecast in a particular location using the Random Forest methodology. Anjana et al. (2021) employ a method of crop yield prediction that involves analysing historical data and utilising a pattern-matching algorithm. A system can utilise several datasets containing information on rainfall, temperature, slope, humidity, and soil moisture in horticulture data to develop a model or approach to provide farmers with a list of recommended crops. This can significantly assist farmers in making informed decisions. van Klompenburg et al. (2020) emphasised the significance of utilising machine learning as a decision support tool for accurately predicting crop production and making informed decisions regarding crop growth during the growing season. According to van Klompenburg et al. (2020), the predominant features utilised in studies include temperature, rainfall, and soil type. Among many machine learning models, the most commonly employed approach is Artificial Neural Networks. Convolutional Neural Networks (CNN) are these investigations' predominant deep learning algorithms.

In contrast, other commonly utilised deep learning algorithms include Long-Short Term Memory (LSTM) and Deep Neural Networks (DNN) (van Klompenburg et al., 2020). Several researchers have utilised machine learning techniques, including regression trees, random forests, multivariate regression, association rule mining, and artificial neural networks, to forecast agricultural yield (Kogan et al., 2018; Cai et al., 2019; Filippi et al., 2019; Bhojani & Bhatt, 2020). Machine learning models see crop production as an implicit function of input variables, such as weather and soil conditions (Bharadiya et al., 2023).

Bharadiya et al. (2023) conducted a comprehensive review on the prediction of crop yield using remote sensing data, agrarian factors, and machine learning techniques. They emphasised the importance of constructing models that establish connections between crop yields and various influencing factors such as weather, soil conditions, terrain, disease, vegetation growth conditions, and human elements like irrigation and fertiliser management. The authors noted that most existing methods for forecasting agricultural yield can provide accurate predictions a few months before harvesting. By utilising remote sensing data obtained across vast regions, it is possible to compute specific parameters. Basso and Liu (2018) observed that yield forecasts primarily rely on field surveys, statistical regressions involving historical yield and in-season variables (such as agrometeorological or remotely sensed data), crop simulation models, or the combination of statistical modelling with dynamic process-based crop simulation models. Field surveys are not commonly used in research to predict crop production, although they are still the primary methods for forecasting and estimating yield in many countries (Basso and Liu, 2018).

An essential aspect of comprehending the potential of agriculture to contribute to general well-being is the examination of agricultural yield and its correlation with the implementation of technology (Boakye, 2023). While emerging technologies are increasingly being incorporated into the agriculture sector, the existing research in agricultural literature primarily concentrates on highly industrialised countries when assessing the impact of these technologies on crop yields (Tolhurst and Ker 2016; Boakye, 2023). Crop production projections have been extensively utilised in North America, Oceania, Europe, and certain regions of Asia. The nations with the highest implementation of yield forecasts include the United States, India, Canada, China, Spain, Germany, Australia, the United Kingdom, Italy, and France (Basso and Liu, 2018).

Advantages and Disadvantages of its Implementation

Throughout the years, ensuring the security of the agri-food sector has emerged as one of the most critical global problems. Implementing sustainable agricultural and food production technology has shown effective in alleviating poverty resulting from increased food demands (Abiri et al., 2023). In recent times, the use of agri-food system technology has significantly altered the global landscape as a result of both external factors and internal influences (Abiri et al., 2023). Digital agriculture (DA) is an innovative technology addressing the worldwide need for sustainable food production. The integration of many sub-branches of data analytics technology, including artificial intelligence, automation and robots, sensors, Internet of Things (IoT), and data analytics, into agricultural operations aims to minimise waste, optimise farming resources, and improve crop yield (Abiri et al., 2023).

The process of acquiring anticipated yield using the survey approach is simple and direct. Surveys can be carried out using interviews and field sampling. The difficulty in forecasting yield at a broad scale using surveys primarily stems from the sample methods employed. Generating valid regional and national yield extrapolated projections by post-processing the anticipated yield at the field scale is likewise difficult (Basso and Liu, 2018). Survey-based operational yield forecasting systems are both time-consuming and labour-intensive.

Furthermore, surveys yield projections that lack long-term predictive accuracy. Using statistical models incorporating agrometeorological, spectral, or agrometeorological variables to predict crop output is reasonably straightforward. The underlying principle of utilising statistical models for crop yield forecasting is based on the assumption that the historical conditions employed in model development would accurately represent the conditions in the forecasting year. Furthermore, it is expected that the forecasted yield under the conditions of the forecasting year can be explained by the same set of independent variables used in the model development, which relied on past years' data (Basso and Liu, 2018). Hence, the development of yield-forecasting statistical models necessitates the availability of high-quality datasets encompassing long-term records of yield and agrometeorological conditions. Meeting such a criterion might be challenging, especially for underdeveloped nations. Their simplicity and low parameter requirements characterise statistical models. However, their ability to give information beyond the range of values for which the model is parameterised is limited (Basso and Liu, 2018).

Enhancements for Predictive Technology in Crop Yield Estimation

Jakku and Thorburn (2010) emphasise the expenses associated with the initial setup and ongoing use of a system, considering its acceptance and economic aspects. Similarly, Li et al. (2020) acknowledge the requirement for costly apparatus. Sayruamyat and Nadee (2020) discovered that farmers depend on outdated technology and have restricted access to cutting-edge sensing technology and advanced mobile devices. Michels et al. (2020) further highlight the absence of high-speed mobile broadband infrastructure in numerous agricultural establishments. Acceptance is essential for technical advancements to have a tangible effect on the world. Nevertheless, adopting technology is multifaceted and frequently misunderstood (Thomas et al., 2023).

The following information is necessary to create an enhanced yield forecasting system: AA precise agricultural land data layer, recognition of field boundaries, identification of crucial crop growth stages using radar data, and rainfall prediction using satellite data. These components are essential elements that must be connected to a crop simulation model. Accurate information about the location and types of cultivated crops is crucial for developing an enhanced forecasting system. The cropland data layers currently accessible are not sufficiently precise for the less developed nations (Vancutsem et al., 2012). Developing a more precise cropland data layer for these countries is crucial. Crop identification plays a dual role in providing both the estimation of crop area necessary for production estimation and the generation of more precise input.

Conclusion

The agricultural and food industries are crucial sectors for the well-being of humanity. The initial agricultural goods serve as inputs in various multi-actor dispersed supply chains, encompassing four distinct clusters or stages of the agricultural supply chain (preproduction, production, processing, and distribution), aiming to reach the end-user or customer. Given the imminent challenges facing the agriculture and food sector, including climate change, population growth, technological advancements, and the state of natural resources such as water, it is imperative to employ digital technologies throughout the agricultural supply chain. This includes automating farm machinery, utilising sensors and remote satellite data, implementing artificial intelligence, and employing machine learning to enhance crop monitoring and improve traceability of agricultural food products.

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