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Review

Progress in Research on Deep Learning-Based Crop Yield Prediction

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Abstract: In recent years, crop yield prediction has become a research hotspot in the field of agricultural science, playing a decisive role in the economic development of every country. Therefore, accurate and timely prediction of crop yields is of great significance for the national formulation of relevant economic policies and provides a reasonable basis for agricultural decision-making. The results obtained through prediction can selectively observe the impact of factors such as crop growth cycles, soil changes, and rainfall distribution on crop yields, which is crucial for predicting crop yields. Although traditional machine learning methods can obtain an estimated crop yield value and to some extent reflect the current growth status of crops, their prediction accuracy is relatively low, with significant deviations from actual yields, and they fail to achieve satisfactory results. To address these issues, after in-depth research on the development and current status of crop yield prediction, and a comparative analysis of the advantages and problems of domestic and foreign yield prediction algorithms, this paper summarizes the methods of crop yield prediction based on deep learning. This includes analyzing and summarizing existing major prediction models, analyzing prediction methods for different crops, and finally providing relevant views and suggestions on the future development direction of applying deep learning to crop yield prediction research.

Keywords: deep learning; prediction model; crop yield prediction

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1. Introduction

Agriculture plays a crucial role in the global economy. Understanding global crop production is essential for addressing the challenges of population growth, food security, and mitigating climate change. Crop yield forecasting stands out as a significant agricultural issue in this context [1]. Crop yield forecasting is a critical aspect of addressing the urgent issue of global food security. By 2050, the world's population is projected to reach 9.3 billion, with a projected 60% increase in demand for food. This necessitates sustainable and innovative agricultural production methods [2]. The conflict between Russia and Ukraine has disrupted global food markets, leading to uncertainty about future harvests and restricting access to essential agricultural inputs such as fertilizers, further exacerbating this challenge [3]. This has sparked concerns among people about the direct and far-reaching impacts on global food security, especially for countries heavily reliant on food imports [3]. Therefore, crop yield forecasting can provide crucial information for developing viable solutions to achieve goals and end hunger [4].

However, crop yield forecasting faces numerous challenges due to many complex reasons. Firstly, crop yields depend on various factors, including soil quality, pests, genotypes, climate conditions, harvest schedules, etc. [5]. Secondly, the process and methods of yield prediction are time-specific and fraught with non-linearity [6]. Within agricultural systems, a considerable portion often eludes depiction through basic stepwise calculations, particularly in scenarios where datasets are complex, incomplete, or ambiguous. Traditional machine prediction methods often employ linear regression, decision trees, and ensemble learning. Linear regression is a simple and commonly used machine learning method that predicts the relationship between crop yield and various influencing factors by fitting a linear model. For instance, historical weather data, soil quality, crop varieties, and other factors can be used to build a linear regression model for yield prediction. A decision tree is a machine learning method based on a tree-like structure, which predicts the target variable by partitioning and assessing the dataset. In crop yield prediction, decision tree algorithms can be used to establish the relationship between crop yield and various factors and make predictions. Ensemble learning, on the other hand, combines the predictions of multiple base models to improve the accuracy and stability of predictions. In crop yield prediction, ensemble learning methods like random forests, gradient boosting trees, etc., can be used to combine multiple decision tree models for yield prediction. However, traditional machine learning methods often have certain limitations when facing these challenges. Machine learning methods typically require manual feature extraction, increasing the need for human intervention. They exhibit weaker performance when handling complex nonlinear relationships or large-scale datasets, potentially leading to underfitting or overfitting issues and requiring significant computational resources and time. For complex tasks, traditional machine learning methods often fall short and necessitate more sophisticated models like deep learning to be handled effectively [7].

In this scenario, deep learning has emerged as a widely applied technology in the agricultural sector because it can effectively handle the spatiotemporal dependencies of data and extract important features without the need for manual feature engineering [8]. Deep learning involves multi-layer neural networks capable of learning abstract features from large datasets, which can be supervised, semi-supervised, or unsupervised. This technology focuses on learning the correlations between functional attributes and interaction factors, which is crucial for accurately predicting crop yields [9]. By leveraging the power of deep learning, agricultural researchers and practitioners can effectively capture complex relationships within the data, leading to more accurate and robust yield predictions. Deep learning algorithms can automatically learn hidden patterns from data and build more effective decision rules. In deep learning, models directly learn to perform tasks from raw inputs such as sound, text, or images, and can achieve extraordinary levels of precision. The deep learning process involves two main steps: training and testing. During the training phase, the model extracts high-level abstract features from labeled data, which helps to improve the accuracy of the results. Because of this capability to feature extraction and pattern recognition, deep learning algorithms often produce more accurate predictions than traditional machine learning algorithms. This makes them particularly useful in fields like agriculture where precision is crucial for forecasting outcomes such as crop yields. Kamilaris and Prenafeta Boldú surveyed 40 research works utilizing deep learning techniques to address agricultural challenges, demonstrating that deep learning provides high accuracy and outperforms existing image processing technologies. This highlights the significant potential of deep learning in revolutionizing agricultural practices by improving precision and efficiency in various tasks, such as crop monitoring, disease detection, and yield prediction [10]. Recent studies have also demonstrated the effectiveness of deep learning techniques in predicting crop yields [9]. In the specific context of crop yield prediction, Bali and Singla proposed a deep learning-based Recurrent Neural Network (RNN) model to forecast wheat production in northern India. They demonstrated the effectiveness of this model, addressing the inherent issue of vanishing gradients [11]. Elavarasan and Vincent introduced a hybrid crop yield prediction system based on deep learning, utilizing deep belief networks and fuzzy neural networks, achieving an accuracy of 93.7% in yield prediction [12]. These studies collectively demonstrate that deep learning techniques have the potential for accurate crop yield prediction by effectively analyzing comprehensive datasets and extracting meaningful insights.

Although some of the literature discusses the utilization of deep learning for crop yield prediction [13–15], and some researchers have compared it with standard machine learning methods and analyzed the influential features [16–18], they have not specifically analyzed the characteristics and limitations of various types of deep learning models themselves. A better understanding of which model is suitable for predicting which type of crop, as well as the characteristics of the model itself, is as important as the prediction itself. Selecting the best-performing deep learning model is closely related to the accuracy of the final prediction. This paper provides a systematic summary of the application of deep learning methods in predicting crop yields, discusses in detail various models of deep learning in agricultural yield prediction, their respective advantages and disadvantages, and lists some major crops suitable for deep learning models. It analyzes the advantages of using deep learning in crop yield prediction and various features affecting crop yield prediction, thus broadening the research perspective for future studies in this field.

The structure of this article is as follows: Chapter Two introduces the concept and practical significance of crop yield prediction; Chapter Three discusses various models of deep learning in agricultural yield prediction, along with their respective advantages and disadvantages; Chapter Four analyzes the advantages of using deep learning models in predicting crop yields for different crops, as well as various features affecting crop yield prediction; Chapter Five elaborates on the challenges and prospects of deep learning in predicting crop yields. Chapter Six summarizes the entire article and presents its conclusions. Figure 1 shows the overall structure of this article.

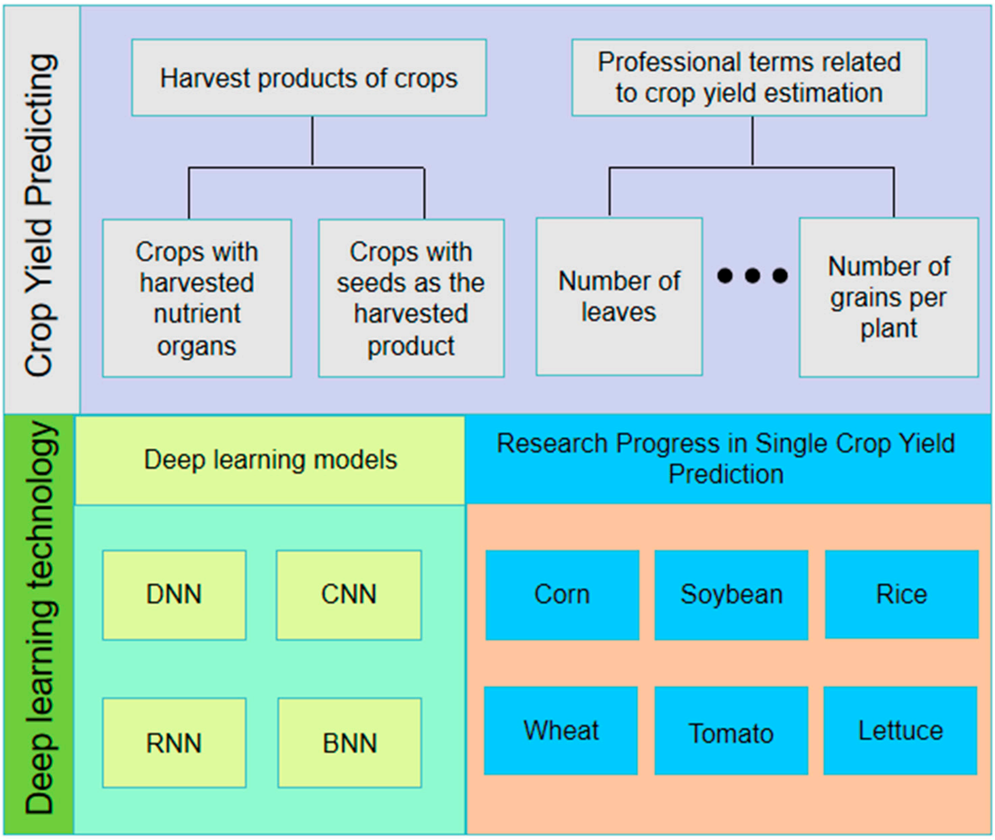

Figure 1. Article Presidential Structure. A Deep Neural Network (DNN) is a type of artificial neural network. A Convolutional Neural Network (CNN) is a specialized type of deep neural network designed for processing grid-like data, such as images. A Recurrent Neural Network (RNN) is a type of neural network designed to handle sequential data by maintaining a form of memory through its internal states. A Bayesian Neural Network (BNN) is a type of neural network that incorporates Bayesian probability to estimate uncertainty in its predictions.

2. Crop Yield Prediction

Crop yield forecasting involves using various data and models to analyze and estimate the quantity or quality of specific crops that may be produced over a future period. This includes considering factors such as climate, soil, crop varieties, agricultural practices, etc., to predict potential changes and trends in yield. Its aim is to provide decision support to agricultural producers, government policymakers, and market participants. Different crops have varying growth cycles and require different environmental conditions, which can affect the biomass and forms of products they can achieve during their growth. This Section describes how different crop forms are defined and introduces some commonly used professional terms related to crop yield estimation.

2.1. Harvest Products of Crops

2.1.1. Crops with Harvested Nutrient Organs

These crops, such as hemp [19], tobacco [20], and fodder crops [21], have stems and leaves as their harvested products. They typically have a concentrated growth period during which plants allocate a significant amount of energy and nutrients to the growth and development of their nutrient organs. Therefore, the management and protection of the plants during this growth period are particularly crucial. Additionally, these crops have relatively short growth cycles and simpler cultivation techniques, as there is no need to balance the contradiction between vegetative and reproductive growth. Especially in the case of green manure fodder crops, maximizing biomass production is the primary goal.

2.1.2. Crops with Seeds as the Harvested Product

Crops such as cereals [22] and dicotyledonous crops [23] exhibit distinct patterns in yield formation. For cereals, the formation of yield components occurs across three distinct stages: pre-anthesis, anthesis, and post-anthesis, with each component overlapping sequentially during the crop's development. Yield components are determined in the order of spike number, grains per spike, and grain weight, with spike and grain formation overlapping. Generally, spike formation initiates at sowing, tillering being the decisive stage, while booting and heading represent consolidation stages. In dicotyledonous crops, such as cotton boll count, rapeseed pod count, and soybean pod count per unit area, depend on plant density and individual plant fruiting. This yield component formation begins from seedling emergence (or transplanting), with the flowering and fertilization process in the mid-late stages being decisive, and the fruit development stage being consolidation. Seed number per fruit initiates floral bud differentiation and is determined during fruit development, with seed set rate often a key factor influencing yield. Table 1 summarizes pertinent crop information along with corresponding explanations.

Table 1. Some commonly used technical terms related to crop yield prediction.

Crop Information	Explanation	Representative Crops
Plant height	The term refers to the vertical height of a crop plant, typically measured as the distance from the ground to the top of the plant, and it is an important indicator reflecting the growth status and architecture of the crop.	Cotton [24] Cotton [25] Soybean [26]
Number of leaves	The term refers to the number of leaves on a crop plant, typically referring to mature, fully functional leaves, and it is used to assess the growth status and photosynthetic capacity of the crop.	Strawberry [27] Banana [28]
Tillering count	The term refers to the number of lateral branches that emerge from the base or stem nodes of a crop plant. The tillering count is closely related to the growth vigor and yield potential of the crop.	Wheat [29] Rapeseed [30]
Hundred-grain weight	The term refers to the weight of a hundred grains of a crop, typically measured in grams. It is an important indicator for evaluating the yield potential and seed quality of the crop.	Corn [31]

Table 1. *Cont.*

Crop Information	Explanation	Representative Crops
Number of branches Spike count	The term refers to the number of branches that develop during the growth process of a plant. It can also be used to describe the growth condition and structural characteristics of the plant.	Cotton [32] Coffee [33]
Number of ears	The term refers to the number of inflorescences or fruit clusters formed by a plant during the growing season.	Wheat [34]
Number of main stem leaves	The term refers to the number of leaves on the main stem of a crop plant, reflecting the growth vigor and photosynthetic capacity of the main stem.	Tomato [35]
Ear length	The term refers to the length of the spike or ear of a crop, typically measured in centimeters. It is an important indicator for evaluating the growth status and yield-forming capacity of the crop's spike.	Corn [36] Wheat, Barley [37]
Ear diameter	The term refers to the thickness or diameter of the spike or ear of a crop, typically measured in millimeters. It is an important indicator reflecting the yield potential and growth status of the crop.	Rice [38]
Number of grains per plant	The term refers to the number of grains or seeds on a single crop plant, which is an important indicator for assessing the yield potential per plant.	Corn [39] Wheat [40]

2.2. Professional Terms Related to Crop Yield Estimation

Understanding professional terminology related to crop yield estimation is crucial for accurate crop yield forecasting. These terms encompass key factors and parameters of crop growth processes. Agricultural professionals can analyze and predict crop yield potential more precisely by accurately comprehending and applying these terms. This precision is vital for decision-makers and agricultural producers as it guides planting decisions, optimizes resource utilization, and formulates effective management strategies to maximize crop yield and quality. Table 1 summarizes some commonly used professional terms related to crop yield estimation, with several typical crop terms serving as input features in the predictive models discussed in Section 4 of this paper.

3. Deep Learning Technology

The inspiration for deep learning models comes from the neural networks in the human brain. Deep learning models typically consist of three layers: the input layer, the output layer, and the hidden/activation layer [41]. To generate predictions, they feed the input through a deep neural network consisting of multiple layers. Each layer analyzes the data to capture distinct features at different levels of granularity or resolution, which are then integrated into more abstract features through a hierarchical process [42]. When traditional linear deterministic models fail to effectively describe the relationship between variables, this approach becomes particularly valuable [43]. In the field of agriculture, the use of deep learning technology has gained momentum due to its ability to handle massive datasets, learn complex relationships between variables, and utilize nonlinear functions [44]. These methods are particularly valuable in extracting features from large datasets, outperforming traditional machine learning approaches in this process [44]. In the context of crop yield prediction, the accuracy of prediction results relies on the extraction of features influencing crop growth, making deep learning a valuable tool in this field [44].

The concept of deep learning can be traced back to the perceptron model in the 1950s, but it did not experience significant growth until recent decades due to limitations in computational resources and data. With the arrival of the big data era and advancements in computing hardware, particularly the use of graphics processing units (GPUs), deep learning has seen rapid development. Deep learning is a cutting-edge tool for data analysis and image processing, with immense potential. It has produced excellent results and has been successfully applied in various industries, including agriculture [10]. The impact of different deep learning models on crop yield prediction depends on the specific application scenario, data quality, and model parameter selection. Considering the strengths and limitations of the models, choosing the appropriate model structure and data processing methods can improve the accuracy of crop yield prediction. From the earliest Deep Neural Networks (DNNs) to later architectures like Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and their important variants such as Long Short-Term Memory networks (LSTMs) and Bayesian Neural Networks (BNNs), each architecture has demonstrated powerful capabilities in specific domains. Currently, the models listed above are widely used in the field of crop yield prediction. For example, Russello utilized a Convolutional Neural Network based on satellite imagery for crop yield prediction. Their model employed 3D convolutions to capture spatiotemporal features and outperformed other machine learning methods [45]. Additionally, researchers like Sharma used a fusion of CNNs and LSTMs to estimate wheat crops. They utilized a raw image dataset in experiments and achieved promising results. The proposed fusion method of CNNs and LSTMs outperformed other convolutional methods with an accuracy of 74% and also surpassed other deep learning models with 50% accuracy [46]. In the following Sections, we will introduce some commonly used deep learning models for crop yield prediction.

3.1. Deep Neural Network (DNNs)

Deep Neural Networks (DNNs) are a specialized type of feedforward neural network with multiple fully connected hidden layers. Their essence lies in establishing and simulating neural networks similar to the thinking patterns of the human brain. Deep neural networks consist of multiple interconnected layers that use nonlinear transformations to process input data, gradually generating more abstract representations as information passes through each layer [47]. Therefore, with increased depth, the network extracts increasingly intricate features, thereby improving result accuracy. Deep neural networks, unlike shallow networks with just one hidden layer, succeed in uncovering the intricate nonlinear connections between input and response variables. Additionally, they alleviate the laborious process of manually crafting features [47]. However, they demand more sophisticated hardware and optimization methodologies for effective training. For instance, the depth of a neural network, determined by the number of hidden layers, notably impacts its performance. While augmenting the hidden layers may mitigate classification or regression errors, it can also introduce challenges like vanishing or exploding gradients, impeding the network's convergence [48,49]. He et al. argued that the primary challenge of deep neural networks is not overfitting but rather the network's architecture [49]. Overfitting issues can be addressed by adding regularization within the network [50]. They proposed a novel deep neural network architecture utilizing residual shortcuts or identity blocks, making optimization of deep networks easier [49]. Similar to traditional Artificial Neural Network (ANN) algorithms, DNNs are also fully connected feedforward neural networks, but with a higher number of hidden layers, making them deeper. Currently, DNNs have been successfully applied to various classification and regression problems [51]. Figure 2 illustrates the structure of DNN. Table 2 summarizes DNNs and their applications.

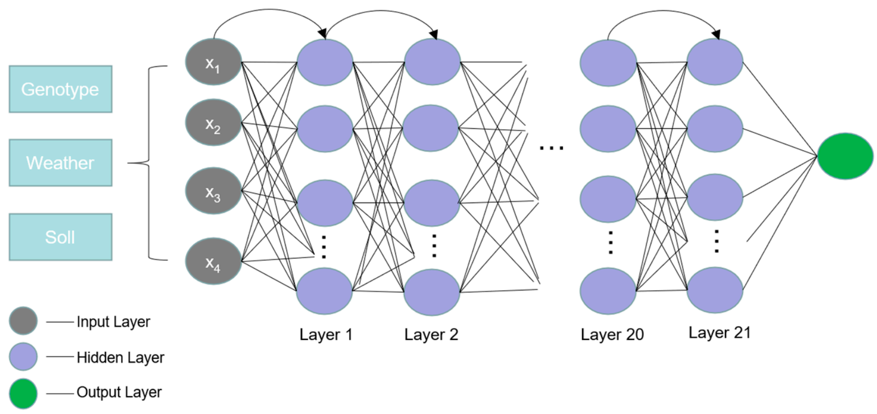

Figure 2. Structure of a DNN.

Table 2. DNNs and their applications.

Crop Type	Deep Learning Model Utilized	Traditional ML Models Utilized	Advantages Demonstrated by Deep Learning	Results or Conclusions	Related References
Seasonal crops in India	DNN	SVM, DT, LR, RF	DNN models are more effective in focusing on function space and reducing model complexity.	An average accuracy of 99.3% can be up to 9 percentage points higher than traditional machine learning models.	[52]
Wheat	DNN	-	DNN models are better suited for handling complex data.	Average absolute error: 76 kg/1000 m^2	[53]
Autumn crops	DNN	SVR, RFR	DNN models can capture complex nonlinear relationships and automatically learn feature representations through their multi-layer structure	The R-squared value of DNN models consistently exceeds that of SVR and RF models, reaching 0.973.	[54]
Corn	DNN	Lasso, SNN, RF	DNN models perform excellently with complex problems and can handle higher-dimensional and more complex data.	The DNN model's root mean square error of 12.81 kg/1000 m^2 outperforms Lasso, SNN, and RF models.	[55]

In crop yield prediction using DNN models, Sobhana et al. proposed an algorithm that utilizes deep neural networks with geographic data to estimate crop yield. They crafted a recommendation system utilizing deep learning algorithms like XGBoost to propose suitable crops, complemented by the creation of a user interface called CROPUP. Their model achieved an accuracy of 99.3% across all seasons and can enhance crop productivity and efficiency when applied [52]. Building upon the aforementioned research, Engen et al. incorporated weather data to forecast the yield of wheat in Norway. They introduced a deep hybrid neural network model to train on this multi-temporal data, combining features from convolutional layers and recurrent neural networks. The results indicate that this model can effectively predict the target, with an average absolute error of 76 kg/1000 m^2 [53]. To compare the predictive performance of the DNN model against others, Dang et al. separately employed support vector regression (SVR), random forest regression (RFR), and deep neural networks (DNN) to forecast autumn crop yield. Ultimately, the coefficient of determination (R-squared) for the DNN consistently exceeded that of the SVR and RF models, achieving 0.973. This led to the conclusion that when trained with a small sample size (e.g., 80 samples), the DNN model outperformed both the SVR and RF models [54]. Khaki proposed a deep learning approach for crop yield prediction, utilizing a deep neural network based on genotype and environmental data to forecast the yield of hybrid maize. The results demonstrate that this model surpasses other well-known methods, including Least Absolute Shrinkage and Selection Operator (Lasso), shallow neural networks (SNN), and regression trees (RT), achieving an RMSE of 12.81 kg/1000 m^2 and a validation correlation coefficient of 0.814 [55].

3.2. Convolutional Neural Networks (CNNs) and Their Variants

CNNs were first created and utilized in the 1980s. At that time, the most notable application of CNNs was for recognizing handwritten digits. Primarily employed in the postal industry for reading postal codes, passwords, and similar data [56]. With the continuous development of deep learning, CNNs have been increasingly applied in the field of agricultural yield estimation in recent years. It is widely applied due to its unique ability to find significant features within data [13]. In contrast to conventional neural network methods, CNNs incorporate specialized layers like convolutional, pooling, and fully connected layers, enabling effective detection of significant data features. Convolutional layers employ convolution operations and activation functions to extract features efficiently [57]. The convolution operation involves filters and feature maps. Filters are a set of weights applied to the input, while feature maps are the corresponding outputs given a filter. Additionally, pooling operations are used for downsampling, as they help effectively detect key features [57]. CNNs possess the capability to analyze diverse data array formats, spanning one-dimensional, two-dimensional, and three-dimensional data, enabling them to capture temporal and spatial dependencies from multi-source datasets such as meteorological and soil data [58]. Compared to traditional feedforward neural networks, CNNs can effectively identify significant features within data. In terms of yield prediction, common variants of CNNs include 2D-CNN, 3D-CNN, and YOLO, among others. Specifically, 2D-CNN is often referred to as a spatial approach, while 3D-CNN is termed as a spatiotemporal approach [18]. In 2D-CNN, input data are viewed as a spatial–spectral volume, with kernels moving across two spatial dimensions encompassing width and height. Yang et al. applied a 2D-CNN deep learning algorithm in crafting a corn yield prediction model. The research found that 2D-CNN exhibits significant advantages in classification and feature extraction [59]. 3D-CNNs can be employed to handle spatial and temporal data, where an additional time dimension is added alongside two spatial dimensions. Nevavuori et al. utilized a spatial–temporal 3D-CNN architecture with time series and multi-temporal data for in-field yield prediction. Compared to other models, the 3D-CNN model demonstrated higher prediction accuracy [60]. The YOLO algorithm is used for real-time object detection. It segments an image into predefined bounding boxes and employs a parallelized recognition algorithm to classify each bounding box into its corresponding object class. The benefits of YOLO lie in its accuracy and speed [61]. Lu et al. developed a soybean yield prediction model utilizing the YOLOv3 deep learning algorithm, which, despite having only half the parameters of ResNet101 (a deep neural network architecture used for image recognition tasks), demonstrates comparable performance. The model effectively predicts the crop's yield [61]. Figure 3 illustrates the structure of a CNN. Table 3 summarizes CNNs and their applications.

Table 3. CNNs and their applications.

Crop Type	Deep Learning Model Utilized	Traditional ML Models Utilized	Advantages Demonstrated by Deep Learning	Results or Conclusions	Related References
wheat and barley	CNN	-	The CNN model can utilize convolutional kernels to capture the local structures and spatial relationships within images.	The CNN model can reasonably and accurately estimate yield based on RGB images, with an average absolute error of 484 kg/ha.	[14]
Corn	CNN	RF	The CNN model outperforms Random Forest in handling complex, high-dimensional, and spatially structured data.	The CNN model has a root mean square error (RMSE) of 958 kg/ha, which is better than that of the Random Forest model.	[62]
Corn and soybeans	CNN	RF, Lasso	The CNN model is sensitive to various factors such as weather, soil, and management, and has successfully predicted yields in untested environments.	The CNN model effectively predicted corn and soybean yields, with an accuracy that is 7 percentage points higher than that of the Random Forest (RF) and Lasso models.	[18]

In crop yield prediction based on CNN models, Nevavuori et al. utilized Convolutional Neural Networks—based on Normalized Difference Vegetation Index (NDVI) and RGB (a color model used for representing and generating colors) data obtained from drones—to establish a crop yield prediction model for wheat and barley. The optimal model predicted field yields with an average absolute error of 484 kg/ha (MAPE: 8.8%). The final results demonstrated that the CNN model could reasonably and accurately estimate yields based on RGB images, providing a specific deep learning model for crops in the continental subarctic climate of Finland [14]. In terms of combining CNN with other models, Shahhosseini introduced an ensemble model comprising multiple hybrid CNN-DNN base learners to forecast corn yields at the county level across the Corn Belt states of the United States. The model incorporates two one-dimensional convolutional neural networks (CNNs) and a fully connected network (FC) in its initial layer, followed by another fully connected network that combines the output of the first layer for the final prediction. This model offers predictions with a root mean square error of 958 kg/ha, providing significant insights for applications in crop yield prediction [62]. Khaki et al. introduced a deep learning framework that integrates CNN and RNN models, offering a hybrid approach to forecast crop yields using environmental data and management practices. According to their comparison, this model effectively predicts corn and soybean yields, demonstrating superior performance over competing models like Random Forest (RF), Deep Fully Connected Neural Network (DFNN), and Least Absolute Shrinkage and Selection Operator [18].

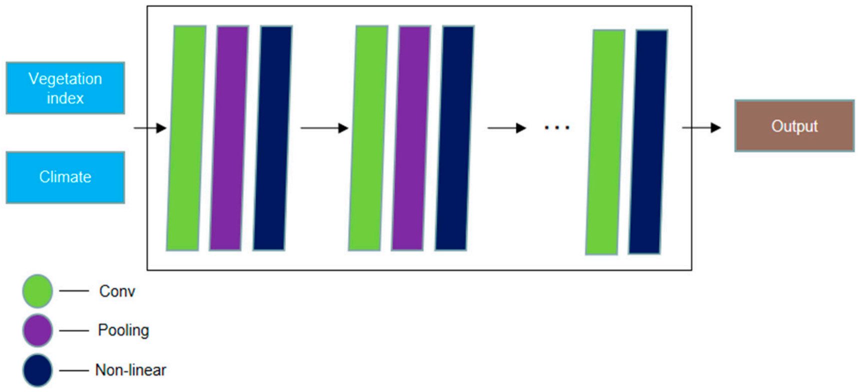

Figure 3. Structure of a CNN.

3.3. Recurrent Neural Network (RNNs) and Their Variants

The recurrent neural network (RNN) is a deep learning method for modeling sequential data. Its core principle involves retaining the output of a layer and feeding it back to the input to predict the output. The retention of information within the hidden state of an RNN enables it to effectively process inputs of varying lengths [16]. Calculations consider historical data, and the model's size does not grow proportionally with the input size. RNNs find utility across diverse tasks including handwriting recognition, image captioning, natural language processing, machine translation, crop yield prediction, and time series analysis [63]. However, RNNs suffer from the issue of vanishing or exploding gradients, making it challenging to capture long-term dependencies during prediction. This implies that when predicting events far into the future from the current time step, the model's accuracy may decrease. Traditional RNN models require fixed-length input sequences. However, in agriculture, there might be time series data of varying lengths, such as different crop growth cycles. Therefore, data may need to be padded or truncated, potentially resulting in information loss or wasting computational resources. Gradient vanishing is a primary issue encountered when using RNNs; it occurs when the gradient of the loss function approaches zero [64]. To address the vanishing gradient problem in RNNs, Long Short-Term Memory (LSTM) networks were developed [65]. They can handle long-term dependencies, storing, and recalling past information [66]. LSTMs excel at capturing temporal dependencies using gradient-based optimization techniques. Structurally, an LSTM is composed of multiple layers, including input, forget, and output gates, along with a memory cell, enabling precise control over cell states and outputs in sequential data processing [56]. These gates function akin to neural network layers, regulating the flow of information within the LSTM architecture [47]. The LSTM gate mechanism facilitates the acquisition of long-term dependencies in sequential data, such as in natural language processing or speech recognition. It achieves this by selectively retaining or discarding information based on its significance to the current task, diverging from standard RNNs, which solely rely on current inputs and past hidden states. This selective memory capability enhances the model's ability to capture intricate temporal patterns. LSTMs can recognize speech features and assist in learning temporal patterns present in data. They demonstrate good transfer learning capabilities and yield high-accuracy yield estimation results [58]. LSTMs can also address issues in high-dimensional data and are effective for time series data. Under limited data conditions, this approach can accurately predict wheat yield [67]. Figure 4 illustrates the structure of an RNN. Table 4 summarizes RNNs and their applications.

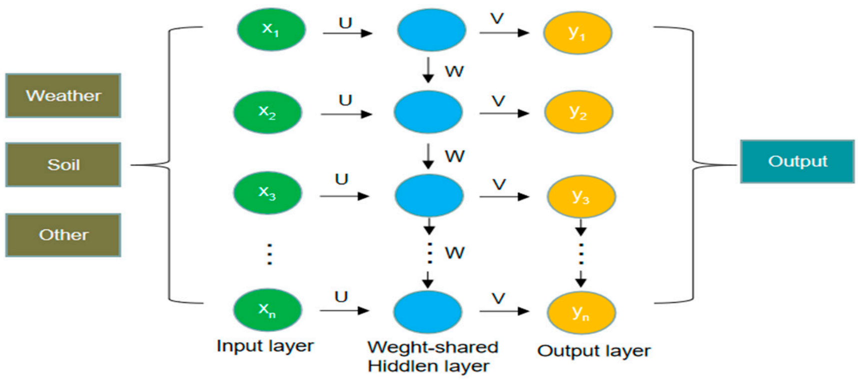

Figure 4. Structure of an RNN.

Table 4. RNNs and their applications.

Crop Type	Deep Learning Model Utilized	Traditional ML Models Utilized	Advantages Demonstrated by Deep Learning	Results or Conclusions	Related References
Corn and soybeans	LSTM	-	LSTM models can directly handle time series data and model long-term dependencies within the sequence.	Compared to general models, location-specific models have a lower average RMSE score, indicating that location-specific methods are more suitable for yield prediction.	[68]
Cereal crops	IOF-LSTM	ANN	The IOF-LSTM model handles underfitting and overfitting issues better than the ANN model.	The introduction of IOF in LSTMs shows advantages in crop yield prediction and accurate forecasting, outperforming machine learning models.	[69]
Rice	Bi-LSTM	MLR, SVM	The Bi-LSTM model can capture dynamic relationships within a sequence through its internal recurrent structure.	The Bi-LSTM model can accurately predict rice yield and outperforms multiple linear regression (MLR) and support vector machine (SVM) methods, with an average error of 25 kg/m^2.	[70]

Priya et al. introduced an attention-based peephole LSTM model designed for crop yield prediction. This model autonomously identifies crucial features from training data, alleviating the challenge of manual feature selection. They used it to predict the maize and soybean yields in the United States and found that the average RMSE score of site-specific models was lower than that of general models, making site-specific methods a better choice for yield prediction [68]. Bhimavarapu et al. introduced an enhanced optimizer function (IOF) to enhance prediction accuracy and integrated it with the Long Short-Term Memory (LSTM) model. They compared this model with eight standard learning methods and found that the performance metrics of IOF-LSTM reached an RMSE of 2.19, and MAE of 25.4. The model exhibited smaller training errors in handling underfitting and overfitting issues. The IOF introduced in LSTM demonstrated advantages in crop yield prediction and accurate forecasting. The reduced RMSE suggests that IOF-LSTM outperforms CNN and RNN in crop yield prediction [69]. Wang et al. developed a rice yield prediction model based on a Bidirectional Long Short-Term Memory (Bi-LSTM) artificial neural network. This model accurately predicts rice yields and outperforms multiple linear regression (MLR) and support vector machine (SVM) methods. The results indicate that the Bi-LSTM prediction model performs well in rice yield prediction, with an average error of 25 kg/m^2 (1 acre = 666.67 m^2) [70].

3.4. Binary Neural Network (BNN)

BNN employs neural networks with Bayesian inference and utilizes probability distributions as weights within the network. The use of Bayesian neural networks helps prevent overfitting issues without the need for excessive validation data to evaluate regularization parameters [71]. Training BNN on large datasets can indeed improve accuracy. Essentially, Bayesian Neural Networks (BNNs) can be understood as regularization by introducing uncertainty into the weights of the neural network. It is akin to ensemble predictions from an infinite number of neural networks with weights sampled from a certain distribution. Bayesian Neural Networks integrate the characteristics of both neural networks and Bayesian methods. They excel at handling uncertainty in data, enabling more comprehensive modeling and inference. Moreover, they perform exceptionally well in small-sample learning by effectively leveraging prior knowledge to aid in model generalization. This capability effectively prevents overfitting and enhances the model's generalization ability. Although the Bayesian Neural Network (BNN) model has relative advantages in agricultural applications, there are also some drawbacks to consider. Bayesian inference typically involves sampling from the posterior distribution of parameters, leading to increased computational complexity, especially with large model scales or extensive datasets. For real-time applications like agricultural yield prediction, high computational complexity might result in slow prediction speeds or an inability to meet real-time requirements. BNNs typically involve hyperparameters such as the choice of prior distributions and sampling methods, which require tuning. Tuning hyperparameters can increase model complexity and often requires a certain level of domain knowledge to effectively optimize them. Figure 5 illustrates the structure of a BNN. Table 5 summarizes BNNs and their applications.

Table 5. BNNs and their applications.

Crop Type	Deep Learning Model Utilized	Traditional ML Models Utilized	Advantages Demonstrated by Deep Learning	Results or Conclusions	Related References
Corn	BNN	-	Binary neural network models can accurately predict corn yields in years with anomalies caused by extreme weather events.	$R^2 = 0.77$	[72]
Corn	BDANN	-	BDANN models excel in handling noise and outliers by using Bayesian inference to adjust model complexity, thus avoiding overfitting.	$R^2 > 0.60$	[73]
Corn	BNN	MLR, SR	BNN can capture more complex nonlinear relationships and feature interactions, whereas SR and MLR models typically assume linear relationships.	An MSE value of 0.448 t/ha shows the smallest error deviation compared to MLR and SR models.	[74]

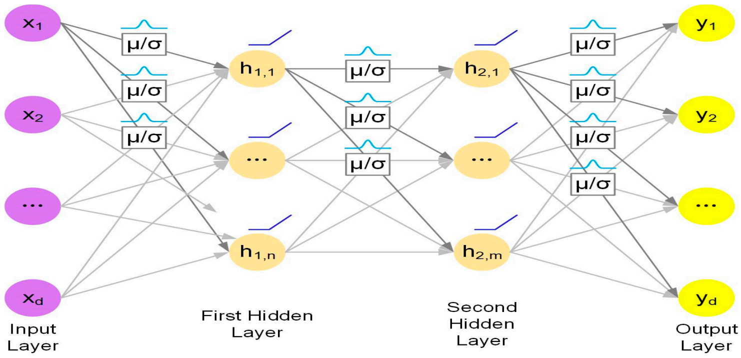

Figure 5. Structure of a BNN.

Ma et al. developed a county-level maize yield prediction model based on Bayesian Neural Networks (BNN). This model not only accurately estimates maize yields in normal years but also accurately predicts maize yields in abnormal years caused by extreme weather events. The average R^2 of the prediction results is 0.77, providing a robust framework for intra-seasonal crop yield forecasting. The study emphasizes the need for a deeper understanding of the impact of environmental stressors on agricultural productivity and crop yield estimation [72]. Ma and Zhang introduced a Bayesian Domain Adversarial Neural Network (BDANN) for unsupervised domain adaptation in counting-level maize yield prediction. By combining adversarial learning and Bayesian inference, BDANN extracts domain-invariant and task-specific features from both the source and target domains, effectively addressing domain shift and ensuring precise maize yield prediction. Their BDANN model achieves an R^2 of over 0.60 in maize yield prediction, demonstrating its superior performance [73]. Aziz et al. employed a Bayesian Neural Network (BNN) approach to analyze predictive models for 12 geographical units, deliberately selecting sampling points and measuring variables such as soil and climate. According to the statistical analysis used, the BNN model demonstrated the highest performance accuracy with an RMSE value of 0.448 t/ha, exhibiting the smallest error bias compared to MLR and SR models. This advancement contributes to the field of rainfed rice cultivation, aiding farmers and agricultural practitioners in making informed decisions and optimizing resource allocation [74].

3.5. Comparative Analysis of Different Models

CNNs, RNNs, DNNs, and BNNs are all deep learning algorithms used for predicting crop yields. DNN models are particularly suited for tasks involving large-scale data and complex nonlinear relationships, capable of learning higher-level feature representations. CNN models have shown significant effectiveness in tasks such as object detection and image classification. RNN models excel at detecting and capturing nonlinear relationships in data over long periods. The prior distribution of BNN models can be chosen based on domain knowledge or the characteristics of the data, thus providing better guidance for model training. Therefore, when selecting a model, it is important to weigh the specific problem and data characteristics, and make a decision based on practical considerations.

The DNN model, with multiple hidden layers, can learn more complex feature relationships and has a stronger capability to model nonlinear data. Therefore, when dealing with large datasets and complex feature relationships, DNNs can provide more accurate prediction results. They are suitable for addressing complex problems in agriculture yield prediction involving interactions among multiple factors. Compared to traditional Artificial Neural Networks (ANNs), DNNs have stronger modeling capabilities and can handle more complex feature relationships. However, they require more computational resources and a large amount of training data, and are susceptible to overfitting issues. For the CNN model, it can handle image and spatial data, automatically extracting and capturing local features, making it well suited for agricultural data with spatial structures, such as spatially distributed soil quality. It can be trained on large datasets within a domain and then fine-tuned on smaller datasets from other domains, facilitating knowledge transfer from one domain to another. This approach can enhance model accuracy when data are limited. In agricultural yield prediction, spatial information such as soil quality and crop distribution is crucial. CNNs excel at capturing spatial features in such scenarios. However, compared to fully connected networks, CNNs may not perform as well with non-spatial data. Additionally, CNN models require a substantial amount of labeled data for training, and the quality of the dataset can significantly impact the model's accuracy. RNNs are suitable for processing time series data such as meteorological data and crop growth data. They can capture long-term trends and cyclical changes in crop growth, effectively incorporating time as a factor. However, they are sensitive to long-term dependencies and periodic patterns, but they have limited ability to fit nonlinear relationships and may not perform well in predicting non-periodic outlier events. The LSTM variant of RNNs effectively addresses the issue of long-term dependencies by controlling information flow through gate structures, resulting in better capture of long-term memory information. It exhibits strong memory performance, capable of retaining and transmitting information over extended periods. When handling long sequence data, it performs better compared to traditional RNN models. RNNs excel in processing sequential data, while CNNs perform better at extracting spatial information. Some studies suggest that combining RNNs and CNNs, such as in a CNN-RNN architecture, can yield better results, particularly in crop yield prediction, leveraging the strengths of both. However, for certain data with temporal characteristics and spatial information, such as video data, relying solely on RNNs or CNNs may not fully exploit the structural features of the data, necessitating the integration of other models or methods for processing. The BNN model provides estimates of uncertainty in predictions, which is crucial for crop forecasting as crop yield is influenced by various factors like weather, soil, pests, and diseases, whose uncertainties affect prediction accuracy. Although BNN models offer advantages in modeling uncertainty and parameter sharing, they face challenges in practical applications such as high computational complexity and difficulty in tuning hyperparameters, which need to be overcome to better leverage their role in crop prediction. Table 6 summarizes the applicable prediction areas in agriculture for these four models and highlights the characteristics of each model.

Table 6. Characteristics and Limitations of Four Deep Learning Models.

Model Category	Applicable Fields	Model Characteristics	Model Limitations	Related References
Deep Neural Network (DNN)	Predictions involving interactions of multiple factors in agricultural yield forecasting: Wheat	A deep neural network with multiple hidden layers can better reveal the fundamental nonlinear relationships between input and response variables. However, this may lead to a reduction in classification or regression errors, thereby impeding the convergence of the neural network.	When data are insufficient, deep neural network models are prone to overfitting the training data, and their complexity makes it difficult to interpret and understand their internal decision-making processes.	[53] [54]
Convolutional Neural Network (CNN)	Suitable for crop prediction with spatial data: Soybeans and Corn	It can effectively identify significant features in the data, particularly adept at handling image and spatial data, automatically extracting and capturing local features. However, it requires a large amount of labeled data for training.	The structure of convolutional neural network models is relatively fixed, making them less suited for handling complex or irregular input data. CNNs require a large amount of labeled data for effective training, and insufficient data may lead to decreased performance.	[18] [62]
Recurrent Neural Network (RNN)	Ideal for crop prediction with time series data: Rice and Wheat	It can effectively handle time series data, capturing long-term trends and periodic changes in crop growth. However, its ability to fit nonlinear relationships is limited.	Recurrent neural network models struggle to capture long-term dependencies. Training on longer sequences requires substantial time and computational resources.	[67] [70]
Binary Neural Network (BNN)	Crop suitable for assessing prediction uncertainty: Corn	It has the advantage of modeling uncertainty and parameter sharing. However, in practical applications, it needs to overcome drawbacks such as high computational complexity and difficulties in tuning hyperparameters.	Binary neural network models may experience a drop in accuracy due to binarization, particularly in complex tasks. The constraints of binarization can cause the model to perform worse on unseen data compared to full-precision models.	[72] [73]

4. Research Progress in Single Crop Yield Prediction

Deep learning techniques have been employed to predict the yield of multiple crops. This paper provides a statistical analysis of crops predicted using deep learning methods, referencing over 200 sources. It provides a detailed introduction and analysis of the main crops involved. The distribution of different types of crops in this study is illustrated in Figure 6, while the data, parameters, models, and results used in yield prediction studies for different crops are presented in Table 7.

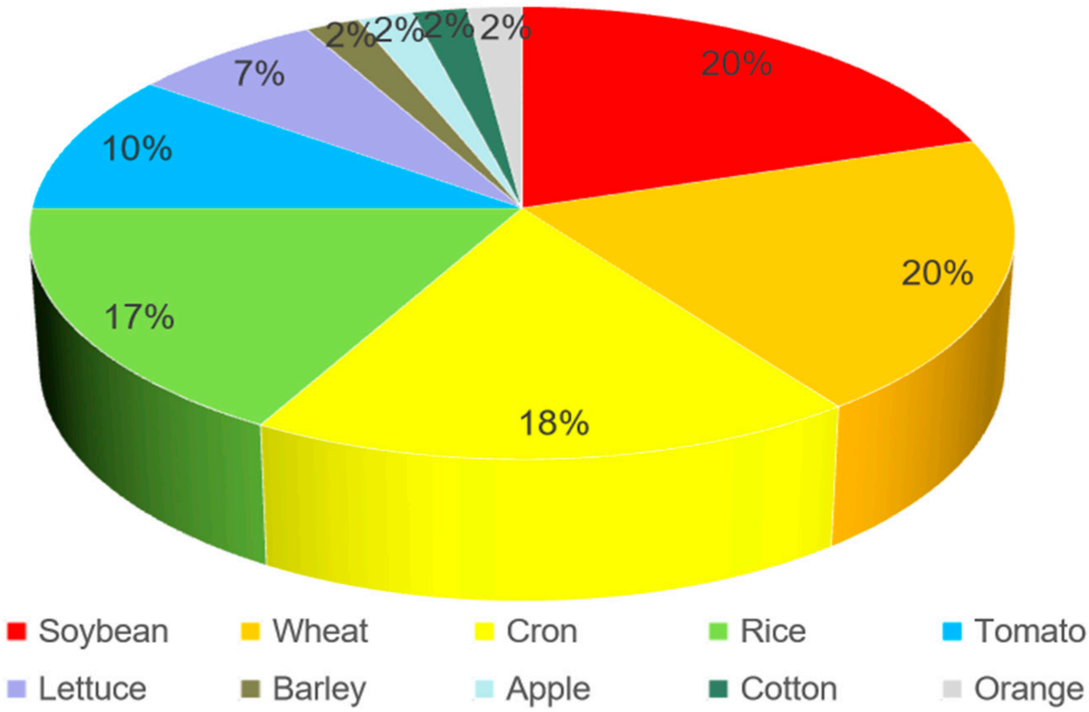

Figure 6. Distribution of different kinds of crops used in reviewed articles.

Table 7. Yield Prediction Research for Six Major Crops.

Crop Categories	Reference Conditions	Deep Learning Models Utilized	Traditional ML Models Utilized	Results or Conclusions	Related References
Corn	Temperature data, soil data	GRU	-	GRU R^2 = 0.98	[75]
Corn	Corn annual planting area, county-level yield, satellite data, and environmental factors	LSTM	LSSSO R^2 = 0.39	DL methods significantly outperform traditional regression models, R^2 = 0.77	[76]
Corn	Regional data, corn trait feature data, meteorological feature data	GAN-GNN	GAN-RF R^2 = 0.84	R^2 = 0.92	[77]
Corn	Corn yield data, climate, and environmental datasets	LSTM, CNN	XGBoost	The XGBoost algorithm outperforms deep learning algorithms in both accuracy and stability	[78]
Corn	Corn yield data, meteorological data, soil characteristic data	CNN-RNN	LASSO, RF	CNN-RNN demonstrates greater effectiveness and advantages compared to LASSO, RF, and DNN models	[79]

Table 7. *Cont.*

Crop Categories	Reference Conditions	Deep Learning Models Utilized	Traditional ML Models Utilized	Results or Conclusions	Related References
Soybean	Weather data, MODIS Land Surface Temperature (LST) data, and MODIS Surface Reflectance (SR) data	LSTM, CNN, CNN-LSTM	-	The CNN-LSTM model outperforms other models, R^2 = 0.74	[80]
Soybean	Soybean plant raw imaging data	GRNN	-	average accuracy = 97.43%	[61]
Soybean	NDVI, WDRVI, EVI, DVI, LSWI, RVI, VARIgreen, SAVI, GNDVI	3D-ResNet-BiLSTM	LR R^2 = 0.708 RF R^2 = 0.499	R^2 = 0.791	[81]
Soybean	Soybean yield data, Phenological information, Satellite products and meteorological data, Soil, irrigation, and location data	LSTM, DNN	XGBoost	XGBoost outperforms other deep learning prediction models under the same input R^2 = 0.82	[82]
Soybean	ENSO index, climate data, and satellite images	LSTM	LR, RF, ANN, XGBoost	Machine learning methods are suitable tools for predicting state and national-level soybean yields based on urban composite levels	[83]
Rice	Satellite data, meteorological data, soil data, agricultural field data, yield data	NN-LSTM, CNN, ConvLSTM	-	RMSE = 89,878	[84]
Rice	Rice yield level data, crop management data, variety and rice growth environment data	CNN	RF R^2 = 0.53	R^2 = 0.76	[85]
Rice	Rice yield and planting area, satellite data, environmental data	LSTM	LASSO R^2 = 0.33~0.42 RF R^2 = 0.76~0.82	R^2 = 0.77~0.87	[86]
Rice	Rice yield data, climate data	BPNN, IndRNN	-	RMSE = 0.0057	[87]
Rice	Rice yield data, meteorological data, RGB image data	CNN	LR	Linear regression accuracy is superior to convolutional neural networks	[88]
Wheat	Satellite data, meteorological data, soil data, farmland data, wheat yield data	CNN-LSTM	-	R^2 = 0.77	[58]
Wheat	Wheat yield data, drone image data	CNN	LR RMSE =1.00	RMSE =0.94	[89]
Wheat	Winter wheat yield and planting distribution data, remote sensing data, meteorological data	BO-LSTM	Lasso R^2 = 0.76	R^2 = 0.82	[90]
Wheat	Spectral data, drone image data, vegetation indices	CNN	RF, KNN, GBR	The CNN model outperforms machine learning models (RF, KNN, GBR).	[91]

Table 7. *Cont.*

Crop Categories	Reference Conditions	Deep Learning Models Utilized	Traditional ML Models Utilized	Results or Conclusions	Related References
Wheat	Crop yield and area data, satellite data, climate data	LSTM	SVR, RF, XGBoost LASSO, RIDGE	Both machine learning methods and deep learning methods outperform linear regression methods.	[92]
Tomato	Main stem node count (N), leaf area index (LAI), total plant weight (W), fruit weight (WF), and mature fruit dry weight (WM)	CNN−RNN	SVR R^2 = 0.9318	R^2 = 0.9995	[93]
Tomato	Tomato growth data, environmental data	CNN	-	Average accuracy: Flower tomatoes = 93.1% Green tomatoes = 96.4% Red tomatoes = 97.9%	[94]
Tomato	Tomato growth data, environmental data	R-CNN	-	R^2= 0.87	[95]
Lettuce	Net weight, dry weight, height, diameter, leaf area	CNN	-	R^2 = 0.88~0.95	[96]
Lettuce	Leaf count, water usage, dry weight, stem length, stem diameter	DNN	ML, SVR, XGBoost	R^2 values all exceed 0.95. The DNN requires fewer input features compared to other models (ML, SVR, XGBoost).	[97]

4.1. Corn Yield Prediction

In their study on corn yield prediction based on deep learning, Ren et al. developed a hybrid approach that combines the WOFOST model with deep learning techniques. They analyzed the potential of yield prediction at different growth stages and features, utilizing machine learning and deep learning methods to design various feature combinations for each growth stage to forecast yield. The final prediction achieved an R^2 of 0.98, with an RMSE of 102.65 kg/ha and an MRE of 1.5. This method significantly improved the accuracy of yield prediction, providing reliable analytical results for yield prediction at different growth stages. Moreover, it addressed the issue of sparse samples, strengthened the agronomy yield prediction mechanism, and offered new insights for yield prediction [75]. To compare with traditional regression models, Zhang et al. employed regularized linear regression (LR) and kernel ridge regression to link EVI and VOD time series, incorporating optical, fluorescence, thermal satellite, and environmental data. They used four data-driven methods—LASSO, Random Forest (RF), XGBoost, and Long Short-Term Memory (LSTM)—to predict county-level corn yield in China. The results demonstrated that deep learning methods significantly outperformed traditional regression models, suggesting that these techniques could open new prospects for crop yield prediction at regional and even global scales [76]. Yang et al. proposed a novel method for predicting corn variety yields based on Generative Adversarial Networks (GAN) and Graph Neural Networks (GNN). This method can accurately predict corn variety yields even when some corn traits are missing. When compared with five commonly used data inference methods, including Random Forest (RF), K-Nearest Neighbors (KNN) regression, Gradient Boosting, XGBoost, and Extra Trees, the model achieved an R^2 value of 0.92, surpassing the other models. This provides a new solution for enhancing the accuracy of large-scale corn variety yield prediction [77]. Kang et al. conducted a comprehensive evaluation of county-level corn yield prediction in the Midwestern United States using various model algorithms, including Lasso, Support Vector Regression, Random Forest, XGBoost, Long Short-Term Memory

(LSTM), and Convolutional Neural Networks (CNN). They utilized an extensive array of environmental variables obtained from satellite observations, weather data, ground model outputs, soil maps, and crop progress reports. The findings revealed that the XGBoost algorithm demonstrated superior performance in terms of both accuracy and stability, overshadowing other methods, including deep neural networks like LSTM and CNN, which did not exhibit notable advantages. This study offers valuable insights into the practical aspects of crop yield prediction and enhances our understanding of how crop yields respond to varying climate and environmental conditions [78]. Sun et al. introduced an innovative multi-level deep learning model that combines RNN and CNN to capture both spatial and temporal features. The model takes time-series remote sensing data and soil attribute data as inputs and produces crop yield as its output. Comparative analysis with the predictive performance of LASSO, RF, and DNN models validates the effectiveness and advantages of this approach [79].

4.2. Soybean Yield Prediction

In their deep learning approach to soybean yield prediction, Sun et al. introduced a CNN-LSTM model designed specifically for forecasting county-level soybean yields at mid-season and end-of-season stages. This model utilizes a combination of crop growth variables and environmental factors, incorporating meteorological data, MODIS Land Surface Temperature (LST) data, and MODIS Surface Reflectance (SR) data, with historical soybean yield data serving as labels for training. Comparative analysis with CNN and LSTM models shows that the CNN-LSTM model achieves RMSE = 353.74 and R^2 = 0.74. Its predictive performance surpasses that of pure CNN or LSTM models for both mid-season and end-of-season predictions. Although the integration of multi-source data with different resolutions and rhythms for feature extraction poses certain challenges, this method holds significant potential for enhancing yield prediction accuracy in other crops such as corn, wheat, and potatoes in the future [80]. Lu et al. proposed a deep learning algorithm based on pod and leaf image recognition, combined with a soybean yield field prediction method using a Generalized Regression Neural Network (GRNN). They utilized GRNN to input leaf count and different types of pods, establishing prediction models for the number of different types of pods in each plant, ultimately resulting in soybean yield. The average accuracy reaches 97.43% [61]. Fathi et al. devised a 3D-ResNet-BiLSTM model to efficiently predict soybean yields across various counties in the United States, aiming to reduce training time. To evaluate the model's effectiveness, they compared its performance with linear regression (LR), random forest (RF), 1D/2D/3D-ResNet models, and a 2D-CNN-LSTM model. The results demonstrated that the proposed 3D-ResNet-BiLSTM model outperformed the other models, achieving significant metrics (R^2 = 0.791). Although further research is needed to fully validate the performance of the 3D-ResNet-BiLSTM model across different geographic regions and environmental conditions, this approach still holds potential for accurately predicting soybean yields and supporting sustainable agriculture and food security [81]. Li utilized a publicly available dataset to develop a soybean yield prediction framework that integrates Extreme Gradient Boosting (XGBoost) with multidimensional feature engineering. They conducted a comparative analysis of this framework with other models for county-level soybean yield prediction, encompassing linear regression (LR), random forest (RF), k-nearest neighbors (KNN), artificial neural network (ANN), support vector regression (SVR), long short-term memory (LSTM), and deep neural network (DNN). The results showed that XGBoost outperformed other prediction models with the same inputs, achieving a coefficient of determination (R^2) of 0.82 and a root mean square error (RMSE) of 0.246 t/ha. In the future, incorporating soybean seasonality into the framework could provide actionable and timely soybean yield forecasts, supporting soybean production assessment and marketing policy formulation [82]. Von Bloh et al. developed a machine learning (ML) model for predicting national soybean production in Brazil. They utilized 20 years of urban soybean production data, remote sensing data, and gridded daily climate data from soybean planting areas in Brazil to train the ML model for estimating urban soybean production. Subsequently, they tested linear regression (LR), random forest (RF), extreme gradient boosting (XGB), artificial neural network (ANN), and long short-term memory (LSTM) models, as well as their ensembles. The results indicated that machine learning methods are suitable tools for predicting state and national-level soybean production based on urban aggregated predictions [83].

4.3. Rice Yield Prediction

In their study on deep learning-based rice yield prediction, Zhou et al. utilized three models, namely, CNN-LSTM, CNN, and ConvLSTM, to forecast the annual rice yield at the county level in Hubei Province, China, considering the spatial heterogeneity across different regions. The experimental results indicated that models incorporating virtual variables representing spatial heterogeneity outperformed those trained solely on remote sensing data. The CNN-LSTM model exhibited superior predictive performance compared to the CNN or ConvLSTM models, with a root mean square error (RMSE) of 89,878 (t), mean absolute error (MAE) of 52,802 (t), and a correlation coefficient (R^2) of 0.934. The study concluded that spatial heterogeneity significantly impacts yield prediction, and the inclusion of custom virtual variables representing county-level information enhances the accuracy of rice yield prediction results. Although the study lacks climate-related features, it still offers valuable insights for rice yield prediction [84]. Building upon the previous study, Tanaka et al. incorporated climate-related features and utilized a convolutional neural network (CNN) approach with RGB images to estimate rice yield, predicting 70% of the variation in rice yield with a coefficient of determination (R^2) of 0.76. This cost-effective, hands-on, and rapid method offers a groundbreaking solution for assessing the impact of interventions aimed at enhancing productivity and identifying areas where such interventions are needed to sustainably increase crop yields [85]. In a comparison between deep learning and machine learning approaches, Cao et al. integrated publicly available data from the Google Earth Engine (GEE) platform, including satellite vegetation indices (meteorological indicators and soil characteristics). They created models using different methodologies—Least Absolute Shrinkage and Selection Operator regression, a machine learning approach with Random Forest (RF), and a deep learning framework based on Long Short-Term Memory (LSTM)—to predict rice yields at the county level across the nation. Results indicated that the LSTM (R^2 = 0.77–0.87) and RF (R^2 = 0.76–0.82) models outperformed the LASSO (R^2 = 0.33–0.42) in yield prediction, with LSTM performing better than RF. This approach could be applicable for estimating crop yields in regions with sparse observational data and on a global scale [86]. Chu and Yu introduced an innovative end-to-end prediction model that integrates two Back Propagation Neural Networks (BPNNs) with an independent Recurrent Neural Network (IndRNN). Utilizing time series meteorological data and regional information, they developed a fusion end-to-end deep learning model to precisely forecast rice yields across 81 counties within the Guangxi Zhuang Autonomous Region of China. Experimental results demonstrated that the model achieved a root mean square error (RMSE)of 0.0057 [87]. Pankaj developed a machine learning-based model for predicting rice yield using simple background DSLR camera images of rice panicles in RGB format. These images were processed to determine the pixel count of panicle area, and various machine learning regression algorithms were compared, including Decision Trees, Random Forests, Support Vector Machines, and Convolutional Neural Networks. Results showed that linear regression outperformed Convolutional Neural Networks (R^2 = 0.97) in accuracy [88].

4.4. Wheat Yield Prediction

In their study on wheat yield prediction using deep learning, Wang et al. developed a dual-branch deep learning model to forecast winter wheat yield in major county-level production areas in China. The first branch of the model employed a Long Short-Term Memory (LSTM) network, taking inputs from meteorological and remote sensing data. The second branch utilized a Convolutional Neural Network (CNN) to capture static soil features. The predictive performance of this model demonstrated good accuracy, with an overall R^2 of 0.77 and RMSE of 721 kg/ha. The method holds significant application potential in various crop types and agricultural landscape regions worldwide [58]. In a comparison between deep learning and machine learning models, Tanabe et al. introduced a CNN model based on multi-spectral images from drones for predicting winter wheat yield. They compared the predictive accuracy of the CNN model with a multi-variate linear regression model based on multi-temporal EVI2. The results indicated that the CNN model had the lowest RMSE (0.94 t/ha), outperforming the best linear regression model (RMSE of 1.00 t/ha) [89]. Di et al. introduced a Bayesian Optimization-based Long Short-Term Memory model (BO-LSTM) and formulated a multi-source data fusion algorithm aimed at extracting crop growth features crucial for winter wheat yield prediction. They proceeded to evaluate the yield prediction efficacy of BO-LSTM against Support Vector Machine (SVM) and Least Absolute Shrinkage and Selection Operator (Lasso) models, employing multi-source data as input variables for comparison. The results indicate that effective deep learning hyperparameter optimization can be achieved through Bayesian optimization. The BO-LSTM model proves to be more effective in capturing data correlations and can attain higher estimation accuracy (R^2= 0.82) in regions with concentrated winter wheat planting distribution and minimal human interference [90]. Li et al. conducted correlation analysis using multi-spectral data from drones during the heading, flowering, and grain-filling stages of winter wheat. They compared the results of machine learning models (Random Forest (RF), k-Nearest Neighbors (KNN), and Gradient Boosting Regression (GBR)) with a deep learning model (1D Convolutional Neural Network (1D-CNN)) for winter wheat yield prediction. The findings revealed that the CNN model achieved the best prediction accuracy across all input variables, outperforming other machine learning algorithms [91]. Liu et al. utilized a comprehensive approach involving six statistical methods, encompassing two linear regression techniques (LASSO and RIDGE), three machine learning algorithms (SVR, RF, and XGBoost), and one deep learning method (LSTM). They integrated satellite variables (coarse-resolution SIFGOME2, high-resolution SIFCSIF, and three vegetation indices) along with climate variables to forecast wheat yield in the Indian Ganges Plain. The findings reveal that the three machine learning approaches and the deep learning method exhibited superior performance compared to the two linear regression techniques. Moreover, both SVR and XGBoost methods outperformed the RF method, emphasizing the substantial benefit of utilizing SIF data for predicting wheat yield, particularly under extreme weather conditions [92].

4.5. Tomato Yield Prediction

In their deep learning-based tomato yield prediction study, Gong et al. introduced a novel method for greenhouse tomato yield forecasting. This method combines the interpretive biophysical model Tomgro with a machine learning model, CNN-RNN. Calibration/training of the Tomgro and CNN-RNN models was performed to predict tomato yield. Additionally, various fusion methods (linear, Bayesian, neural networks, random forests, and gradient boosting) were employed to merge the predictions from individual models, resulting in the final prediction. Experimental results demonstrated that the CNN-RNN model outperformed the machine learning models, achieving highly accurate predictions (R^2 = 0.9995). This validates the applicability of the model for greenhouse crop yield prediction under controlled conditions. Leveraging greenhouse climate data and historical crop yield information, the model can forecast future crop yields [93]. Ge et al. proposed a tomato counting method based on object tracking algorithms, using an improved YOLO model combined with an object tracking algorithm based on deep feature extraction networks to predict tomato yield. The experimental results show that this algorithm effectively prevents double counting and achieves excellent practical results. The mean average precision was 93.1% for flowers, 96.4% for green tomatoes, and 97.9% for red tomatoes. This approach demonstrates the potential for accurate yield estimation through computer vision and deep learning, providing valuable insights for agricultural management and crop production planning. The combination of object detection and tracking allows for efficient and accurate counting of tomatoes in various stages of growth, contributing to better yield prediction and resource allocation in tomato cultivation [94]. Mu et al. utilized a faster Region-based Convolutional Neural Network (R-CNN) to construct a tomato detection model, employing deep learning techniques to automatically detect ripe green tomatoes. The findings indicate that this approach notably boasts higher accuracy in tomato counting (R^2 = 0.87), holding significant potential for maturity and yield prediction [95].

4.6. Lettuce Yield Prediction

In deep learning-based lettuce yield prediction, Gang et al. devised a two-stage CNN model leveraging RGB and depth images to accurately estimate lettuce yield in a greenhouse hydroponic setup. The integration of RGB-D images with a CNN-based architecture demonstrated efficacy in assessing the growth index of greenhouse lettuce, suggesting that the CNN model constructed with RGB-D images offers non-destructive, swift, and precise measurements of the lettuce growth index. The results showed that the established model achieved an R^2 of 0.95 for predicting the yield dry weight of lettuce, suggesting that the proposed model also aids in forecasting the optimal harvest period and development of crops [96]. Mokhtar et al. employed four machine learning (ML) models, namely, Support Vector Regression (SVR), Extreme Gradient Boosting (XGB), Deep Neural Network (DNN), and Random Forest (RF), to predict the yield (fresh weight) of lettuce. The results indicated that the correlation coefficients of all four models exceeded 0.95. However, the DNN had fewer input features compared to the other models, making it the preferred choice. This study's methodology holds promise for scaling up crop yield prediction by enhancing it through the incorporation of climate variables, agricultural management data, and higher-resolution spatiotemporal input variables [97].

This Section delved into recent research on yield prediction using deep learning, focusing on six major crops: maize, soybean, rice, wheat, tomato, and lettuce. It compared traditional machine learning algorithms with deep learning methods. The findings suggest that for predicting yields of individual crops, certain models tend to be more suitable. For instance, LSTM models were frequently used and yielded more accurate results in soybean yield prediction, whereas CNNs were predominantly used in wheat yield prediction. Overall, deep learning models generally provide more accurate predictions compared to traditional machine learning models. However, in a few cases, machine learning predictions also outperformed deep learning models. Therefore, testing models with varying feature sets and complexities is crucial to identifying the best-performing model.

5. Challenges and Development Directions in Crop Prediction

5.1. The Challenges Facing Crop Yield Prediction

Crop yield prediction is of great significance in agricultural production, yet it faces numerous challenges. These challenges can be mainly categorized into the following aspects.

Data Acquisition: Agricultural systems, climate conditions, and crop types may vary across different regions, hence the need to consider geographical coverage differences. When conducting crop prediction across regions or countries, integrating data from different regions and considering interregional differences is necessary. This includes challenges related to collecting and ensuring the quality of various data such as soil conditions, climate data, and crop growth. Data quality is crucial for the effectiveness of deep learning, yet obtaining high-quality data is not easy. There may be noise, missing values, or incomplete data, which can impact the performance of the model.

Influence of Natural Conditions: Crop yields are affected by a variety of factors such as climate, pests, diseases, and soil nutrients, all of which interact in complex ways, making it challenging to develop predictive models. Climate change and natural disasters introduce significant uncertainty, making crop yield prediction more difficult and impacting the accuracy of long-term forecasts. The complexity and diversity of natural conditions make it challenging for models to capture all the changes and characteristics. Building accurate and reliable crop yield prediction models is a complex task, requiring consideration of multiple factors in agricultural production, while existing models still have certain limitations.

Model Selection: Training deep learning (DL) models require significant time, especially when the model contains many layers, and the performance of the model may vary depending on certain factors. The most complex models may not necessarily yield the best performance; instead, they can make algorithms more challenging. Choosing the appropriate crop prediction model requires a comprehensive consideration of data conditions, prediction needs, and model characteristics, often necessitating model comparison and evaluation. When selecting a model, additional considerations include model interpretability, computational efficiency, data requirements, and feasibility for real-world applications.

Model Interpretability: Deep learning models are typically black box models, making it difficult to explain the reasons behind their prediction results. This may not be ideal for farmers and decision-makers who need to understand the factors and logic behind the prediction results. Therefore, when applying deep learning to crop yield prediction, further research and development of models with strong interpretability are needed.

5.2. The Future Direction of Crop Yield Prediction

Future agricultural yield forecasting will encounter numerous challenges and opportunities, with key directions including the following aspects:

a. In the future, continuous optimization of deep learning model structures and algorithms will be crucial advancements in predicting crop yields. These models utilize big data to analyze soil, climate, and plant growth data, better capturing patterns and features within the data. This will enhance the precision and efficiency of crop yield prediction and management. Introducing more layers, complex connectivity patterns, or effective parameter tuning methods will improve the models' ability to understand complex data relationships, aiding farmers in maximizing yields while minimizing resource consumption. Advances in prediction models will make agricultural production more sustainable, addressing global food security challenges and paving the way for innovative developments in agricultural forecasting.
b. Integrating multi-modal data will also be a key direction for the future development of yield forecasting. Advances in agricultural yield estimation will delve into the integration of multi-layered data sources. This encompasses combining satellite imagery and drone data with ground-based sensor information, along with leveraging meteorological data and IoT sensor inputs through multidimensional fusion. Through this multi-modal data integration, it becomes possible to achieve multiscale monitoring and fine-grained analysis of farmlands, thereby enhancing the accuracy of crop yield predictions. Additionally, employing data mining and artificial intelligence techniques to effectively integrate information from different data layers can provide more scientific bases and precise guidance for crop estimation. This direction not only contributes to increasing crop yield and quality but also optimizes resource utilization effectively, promoting the shift toward intelligent and sustainable agricultural production.
c. The application of transfer learning and reinforcement learning techniques is also advancing toward greater intelligence, flexibility, and efficiency. In future developments, transfer learning can expedite the customization and optimization of deep learning models in agriculture by leveraging existing data and models from other domains. This enhances adaptability and efficiency across different crops, regions, and environmental conditions. For instance, patterns and influencing factors learned from wheat or growth data can be applied to rice prediction, potentially aiding prediction for crops with limited data in the future. In scenarios with significant agricultural seasonality and environmental fluctuations, transfer learning will bolster adaptability to new datasets by leveraging knowledge from existing datasets, thereby improving prediction stability and accuracy. Meanwhile, reinforcement learning demonstrates significant potential in optimizing crop yields. By establishing interactive mechanisms between models and the environment, reinforcement learning autonomously learns

and adjusts optimal decision strategies. This promises more precise adaptation to complex agricultural environments and variable climatic conditions, offering new intelligent solutions for agricultural production.

d. Explainable modeling holds significant importance for the future development of agricultural yield estimation. As agricultural data volume and complexity increase, decision-makers need to understand and interpret the predictive outcomes and their underlying reasons. In the future, explainable modeling will focus on elucidating complex data patterns and predictive outcomes in a simple and understandable manner, particularly in areas such as crop growth, soil texture, and water distribution forecasts. These models not only provide accurate predictions but also convey the logic and causal relationships behind the models to agricultural practitioners and policymakers, aiding them in making more effective decisions.

6. Conclusions and Outlook

This paper provides a systematic review of crop yield prediction research based on deep learning over the past five years. The paper categorizes and organizes existing prediction methods based on the significance of crop yield estimation, the deep model algorithms used, and the prediction methods for different crops. First, the article explains the concept of crop yield estimation, describing how different forms of crop yield are defined and providing definitions for various professional indicators related to yield estimation. Next, it summarizes the characteristics and application examples of deep learning models commonly used for crop yield prediction, such as DNN, CNN, RNN, and BNN. Among these, DNN models feature multiple hidden layers, enabling them to learn more complex feature relationships and exhibit stronger capabilities in modeling nonlinear data. The CNN algorithm has shown significant effectiveness in tasks such as object detection and image classification. RNN can effectively detect and capture complex and nonlinear relationships in data over long sequences. BNN models can provide estimates of uncertainty for prediction results. Next, the paper delves into the six crops that have drawn the most attention in recent deep learning-based yield prediction studies: corn, soybeans, rice, wheat, tomatoes, and lettuce. It provides a detailed summary of the input features, model algorithms, and comparisons of various methods used for crop yield estimation in these cases. The paper also compares traditional machine learning algorithms (e.g., random forests, neural networks, linear regression) with deep learning algorithms (e.g., DNN, CNN, RNN, BNN) in a vast array of yield prediction studies. The results indicate that in most cases, deep learning models provide more accurate predictions than traditional machine learning models. However, to find the best-performing model, it is also important to test models with varying numbers of features and complexities. Finally, the paper analyzes the challenges facing crop yield estimation in the future, as well as the development trends in this field. Challenges in crop yield prediction extend beyond data acquisition and model selection to include the impact of climate change. Climate conditions are a crucial factor affecting crop yield, but climate change is a gradual and evolving process. Historical data may differ significantly from current climate conditions, posing a challenge to model prediction accuracy. To improve prediction precision, models must adapt to climate change trends and incorporate new climate data. Additionally, genetic factors influence crop yield over the long term, but genetic traits of varieties may evolve with advancements in breeding technology. Historical data may not fully capture the impact of new crop varieties or genetic improvements on yield. Therefore, when using historical data for prediction, it is essential to account for these genetic changes. Dynamic updating mechanisms or incremental learning methods can help models adjust parameters as genetic data are updated, maintaining sensitivity to the latest information. In terms of future development, further algorithm optimization of deep learning models will enhance their predictive capabilities and robustness. This will involve introducing deeper and more complex neural network architectures, as well as customized algorithms tailored to crop growth characteristics, thus improving the accuracy of yield predictions. By integrating multiple data sources such as remote sensing imagery, meteorological data, soil characteristics, etc., and employing multi-modal data fusion techniques, useful information can be extracted and analyzed from diverse data types. This facilitates a more accurate assessment of crop yield potential. Fine-tuning parameters based on pre-trained models using transfer learning can further enhance a model's generalization capability and adaptability, yielding better performance when addressing new problems. Additionally, focusing on modeling uncertainty in predictions can facilitate effective estimation of uncertainty in prediction outcomes, thereby improving the credibility and interpretability of predictions.

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