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A Survey on Deep Learning Based Crop Yield Prediction

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ABSTRACT

Agriculture is the most important sector and the backbone of a developing country's economy. Accurate crop yield prediction models can provide decision-making tools for farmers to make better decisions. Crop yield prediction has challenged researchers due to dynamic, noisy, non-stationary, non-linear features and complex data. The factors that influence crop yield are changes in temperature and rainfall, plant disease, pests, fertilizer, and soil quality. The paper discusses the factors affecting crop yield, explores the features utilized, and analysis deep learning methodologies and performance metrics utilized in crop yield prediction.

INTRODUCTION

The most important sector in growing nations like India is agriculture. In addition to food, agriculture provides raw materials for many industries, like textiles, jute, sugar, tobacco, and vegetable oil. The importance of agriculture can be understood from the fact that almost 60% of the employment in India is related to agriculture, contributing to 17% of the gross domestic product in India. Crop growth monitoring and yield estimates are essential for a country's economic success. It immediately influences international and national economies and plays a significant role in food security and management. Farmers need an effective crop yield prediction method to determine what crop to grow in a particular field and when to grow that crop. Yield prediction used to be done by considering a farmer's previous experience with a specific field and crop (Nevavuori et al. 2019). When making decisions about agricultural risk management and predicting the future, it is essential to have precise knowledge about crop production history. Many factors influence crop yield, including plant diseases, environmental factors, soil quality, genotype, insect infestations, water quality and availability, and harvest activity planning (Elavarasan & Vincent 2020). Plant diseases are a worldwide hazard to food security and management, but they can be incredibly destructive to small-scale farmers who rely on healthy crops for their income (Chu & Yu 2020). When these factors are not adequately monitored and managed, they can pose a substantial risk to farmers (Saravi et al. 2019). The main aim of predicting the yield of crops is to increase crop production. Many well-developed models are used to attain this goal (Cao et al. 2021a). Recent developments include crop yield prediction models that use deep learning and machine learning techniques to increase crop productivity. As a part of artificial intelligence, machine learning algorithms, and deep learning algorithms appear to have improved yield prediction and the ability to evaluate large amounts of data.

Machine learning algorithms are a subset of AI programs that give more accurate results in software applications without being specifically designed to do it (Rashid et al. 2021). An ML model is established with a few parameters and learning. Learning is executing a program to optimize the model's parameters using training data or prior experience (Paudel et al. 2021). The model could be predictive to make future predictions, descriptive to learn from data, or both. Due to their efficiency and prediction accuracy, many ML algorithms have been used to handle complex problems such as forecasting, fault detection, resource management, pattern recognition, and robotics in these highly dynamic times. Reinforcement learning, unsupervised ML, unsupervised ML, and semi-supervised ML are the four main approaches of ML algorithms. ML algorithms can discover knowledge from datasets by identifying patterns and correlations for improving crop yield predictions (Van Klompenburg et al. 2020). Decision support tools are essential for crop yield prediction to decide which crops to cultivate and what to do with them while growing. Recently, ML approaches such as decision trees, stepwise multiple linear regression, multivariate regression, applied decision trees, and weighted histogram regression have been used in yield prediction (Abbas et al. 2020). ML's significant limitations are difficulty finding optimal features, limited learning from data, and low prediction efficiency of crop yield. So, DL (deep learning) algorithms are used to estimate the yield.

A deep learning algorithm is part of an ML algorithm used to perform complex computations on large volumes of data in sophisticated ways (Muruganantham et al. 2022). A neural network is made up of artificial neurons called nodes. Nodes are arranged as input, hidden, and output layers. Each node receives information in the form of inputs from data. The inputs are multiplied with random weights, adding a bias to the results. Finally, activation functions are used to decide which neuron should fire. DL algorithms can automatically learn hidden patterns from the data and construct more efficient decision rules. In DL, a model learns to perform tasks directly from sound, text, or pictures and can achieve remarkable precision. The DL process consists of two main steps: testing and training. The training phase can be used to label large volumes of data and identify their similar features. As a result, the model extracts the features and contributes to increasing the accuracy of the results. The model uses its gathered knowledge to render unexposed data and labels during testing. DL algorithms produce more accurate predictions than traditional ML algorithms (Elavarasan & Vincent 2021). DL is used in various applications like crop yield prediction, natural language processing, fraud detection, visual recognition, entertainment, news aggregation and fraud news detection, self-driving cars, virtual assistants, and healthcare. Due to many complex factors, crop yield prediction has been challenging for researchers. For example, environmental factors like weather data have nonlinear and non-stationary data, which is difficult to estimate.

The DL algorithms handle the spatiotemporal dependency in a dataset in an effective manner (Tian et al. 2021a). Many studies have used DL methods such as RNN, CNN, LSTM, MLP, and autoencoders to predict crop yield. The DL algorithms can identify the important features of data without the need for handcrafting input data. The vanishing gradient problem may occur in deeper networks, which can be addressed by a Long Short Term Memory network (Liu et al. 2022). Other techniques like stochastic gradient descent, dropout, and batch normalization have been created to increase the performance and accuracy of DL models. DL algorithms can improve performance, but there is a lack of literature on the issues of applying DL techniques to estimate crop yields. Crop yield prediction depends on the data source, crop type, and DL algorithm.

MATERIALS AND METHODS

There are two steps to the bibliographic analysis in crop yield prediction: (a) to collect papers related to crop yield prediction and (b) to analyze and review the papers in detail. The resources for this study were collected from IEEE Xplore, Science Direct, Springer, MDPI, Wiley, and IOP scientific databases. The following query ["deep learning"] AND ["yield prediction"] OR ["yield estimation"] is used as a search keyword to filter out papers referring to deep learning and the agricultural domain. From this effort, a total of 48 documents were found for analysis and review. The entire process of this review is based on the research questions. The significant role of research questions is to analyze and explore all the dimensions of the studies. The following 5 research questions are listed in this study.

- RQ1: What are the features used for crop yield prediction?
- RQ2: What are the data sources used to predict crop yield?
- RQ3: What kinds of crops are used in yield prediction using deep learning algorithms?
- RQ4: What deep learning approaches have been applied to predict crop yield?
- RQ5: What are approaches used to evaluate the performances of deep learning algorithms?

Factors Affecting Crop Yield Prediction

Crop yield is influenced by multiple factors like soil fertility, water availability, climatic conditions, plant diseases, and pets are the most critical factors influencing crop productivity. When these factors are not monitored and handled correctly, they can cause considerable risk to farmers. Soil fertility is soil's ability to supply nutrients necessary for a crop's optimal growth (Elavarasan & Vincent 2020). A total of 17 nutrients are required for healthy crop growth. Each nutrient is equally necessary to the plant's development but in varying proportions. Due to these variations, the critical elements have been grouped as key sources of micronutrients such as Mo, Cl, Fe, Mn, B, Ni, Cu, and Zn and macronutrients like O, P, C, N, K, S, H, Mg, and Ca (Elavarasan & Vincent 2021). Plant nutrients include root, leaf, fruit development, chlorophyll, protein and hormone production, and photosynthesis. Because soil fertility is a primary source of these nutrients for plants, nutrient content in soil can significantly impact crop yield. Any one of these nutrient deficiencies can reduce crop production by affecting the growth factor of the crop. The amount of water and crop yield is strongly interrelated.

Water significantly impacts crop productivity and is considered the world's most important agricultural input. Throughout a plant's lifespan, it requires large volumes of water to perform processes like photosynthesis, translocation, utilization of mineral nutrients, respiration, cell division, and absorption. Both excessive and insufficient water has a significant impact on yield quantity and quality. When too much water is on a farm, the roots can decay, and the crops will not get sufficient oxygen from the soil. When there is insufficient water on a farm, the plant does not receive the necessary nutrients. As a result, both water scarcity and excess water on fields can equally impact crop growth and development, yield, and quality. Solar radiation and temperature are other essential elements affecting crop growth, development, and yield. All plants have maximum, optimum, and minimum temperature limits (Jeong et al. 2022). High temperatures influence plant growth in a variety of ways. When the temperature rises, the activities of photosynthesis and respiration increase. When temperatures rise above a certain threshold, the two processes become imbalanced, affecting mineral nutrition, pollen formation, and shoot growth, resulting in a reduced yield. Low temperatures impact crop growth characteristics, including cell division, water transport, survival, photosynthesis, growth, and yield.

When an organism infects a plant, it disturbs its normal growth tendencies. Symptoms might range from minor discoloration of plants to the plant's death. Common plant diseases include blight, gall, canker, leaf curl, root rot, chlorosis, leaf spot, stunting, wilt, and powdery mildew. Microorganisms that can damage and cause plant diseases include bacteria, fungi, and viruses. Crop yield is also influenced by several soil-borne and above-ground insect pests. Pathogens negatively impact crop yield and soil quality and can harm plants in various ways (Lee et al. 2019). Aside from causing direct damage to crops, pests can also harm plants in other ways, such as by destroying plant roots, which affects the plant's ability to absorb water and nutrients.

Classification of Features Used in Crop Yield Prediction

The features employed with the DL approaches used in the

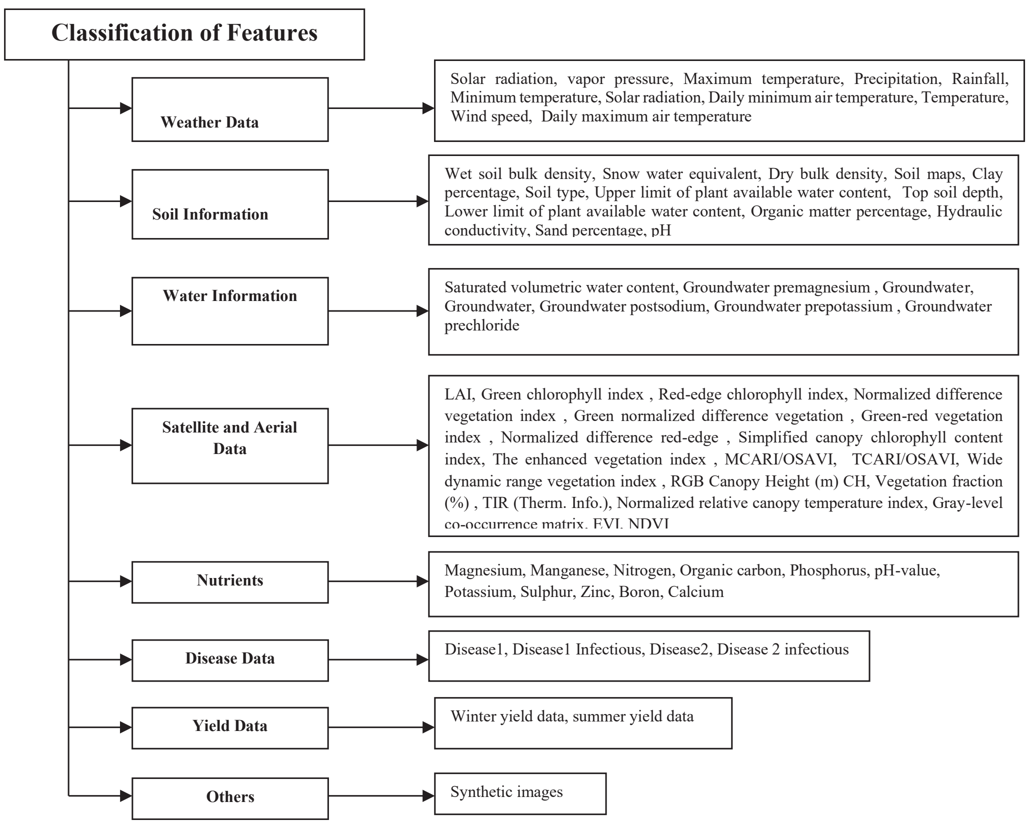

Fig. 1: Features categorization for crop yield prediction.

articles were analyzed and presented to answer research question one (RQ1). The massive amount of data features employed in yield estimation better understanding of the features. The features were grouped into six categories: weather data, soil information, water information, satellite and aerial data, nutrients, crop disease data, yield data, and others. The categorization of features is shown in Fig. 1.

For example, all data features related to satellite and aerial data were grouped, and data features like saturated volumetric water content, groundwater magnesium, groundwater sodium, groundwater potassium, and groundwater chloride were placed in a group with water information. Soil-related features like wet soil bulk density, snow water equivalent, clay percentage, dry bulk density, the lower limit of plant-available water content, an upper limit of plant-available water content, organic matter percentage, hydraulic conductivity, soil maps, pH, soil type, and topsoil depth were grouped with soil data in one category. Weather-related features like maximum temperature, solar radiation, minimum temperature, vapor pressure, rain, solar radiation, temperature, wind speed, precipitation, daily maximum air temperature, and daily minimum air temperature were grouped with weather data. Disease data, yield data, and synthetic images were placed under one group with the name of others. Features and datasets used in the articles to predict crop yields to answer research question two (RQ2) are displayed in Table 1.

The distribution of the data features of the group in the reviewed articles is shown in Fig. 2. The data features related to satellite and aerial data and weather conditions were commonly used in most articles. Satellite images are less expensive and more accessible. It is easy to scale across a large area (Petersen 2018). The MODIS

Table 1: Summary of features utilized in reviewed articles.

Authors	Data Set	Weather Data	Satellite and Aerial Data	Soil Information	Water Information	Yield Data	Nutrients	Disease Data	Synthetic Image
Alibabaei et al. (2021)	Climate data from the agricultural weather station in Portugal, Fadagosa dataset.	√				√			
Bhojani & Bhatt (2020)	wheat yield data from the Directorate of Agriculture, Gandhi nagar, weather datasets from the Agro meteorology Department, Gujarat	√				√			
Cao et al. (2021a)	MODIS dataset, TerraClimate dataset	√	√	√					
Cao et al. (2021b)	Agricultural Statistical Yearbook, ChinaCropPhen dataset, CSIF dataset, TerraClimate datasets, Soil particle-size distribution dataset	√	√	√		√			
Chu & Yu (2020)	Rice yield data, meteorology data in the Guangxi Zhuang Autonomous Region, China	√				√			
Elavarasan & Vincent (2020)	Climatic data from the Indian meteorological department using the METdata tool.	√		√	√		√		
Elavarasan & Vincent (2021)	Meteorological data were collected using the METdata tool from the website of the Indian Meteorological Department.	√		√	√		√		
Gao et al. (2020)	MODIS Dataset, climate data from the Daily Surface Weather and Climatological Summaries (DAYMET) databases, and soybean and maize yields from the USDA Quick Statistic Database.	√	√			√			
Jeong et al. (2022)	MODIS, COMS MI, RDAPS, IRRI Paddy Map	√	√			√			
Jiang et al. (2020)	MODIS Dataset	√	√	√					
Khaki & Archontoulis (2020)	USDA-NASS, Daymet, Gridded Soil Survey Geographic Database	√		√	√	√			
Khaki & Wang (2019)	Syngenta Crop Challenge dataset in the US and Canada spanning 8 years of data.	√		√		√			
Khaki et al. (2021a)	yield performance dataset between 2004 and 2018 in US Corn Belt, Satellite data- MODIS(MOD09A1 and MYD11A2) crop-specific land cover data- USDA-NASS cropland data layers	√	√	√		√			
Lee et al. (2019)	PlantVillage dataset	√			√			√	
Liu et al. (2022)	satellite-based SIF Dataset, MODIS Dataset, TerraClimate Dataset	√	√			√			

Table Cont....

Authors	Data Set	Weather Data	Satellite and Aerial Data	Soil Information	Water Information	Yield Data	Nutrients	Disease Data	Synthetic Image
Ma et al. (2021)	MODIS Dataset, Parameter elevation Regressions on Independent Slopes Model dataset, Soil Survey Geographic Database	√	√	√		√			
Nevavuori et al. (2019)	Temperature data from the Finnish meteorological department, Sentinel – 2A Data, UAV images.	√	√			√			
Nevavuori et al. (2020)	Meteorological data from the Finnish meteorological institute for the Pori area, UAV images	√	√			√			
Qiao et al. (2021)	Satellite data- MODIS(MOD09A1 and MYD11), Yield data collected from Agricultural statistic yearbook		√			√			
Rahnemoonfar & Sheppard (2017)	Synthetic Image								√
Sagan et al. (2021)	WorldView-3 and PlanetScope satellite data	√	√						
Saravi et al. (2019)	DSSAT weather file	√			√	√			
Schwalbertet al. (2020)	MODIS dataset, soybean yield data from IBGE	√	√			√			
Shahhosseini et al. (2021)	corn yields data from USDA National Agricultural Statistics Service	√		√		√			
Sun et al. (2019)	MODIS SR data MODIS LST data Daymet Weather Data	√	√						
Teodoro et al. (2021)	multitemporal–multispectral dataset		√						
Tian et al. (2020)	MODIS Dataset.		√			√			
Tian et al. (2021a)	MODIS products (d60-d152), wheat yield data from the Shaanxi Rural Yearbooks data, meteorological data from the China Meteorological Administration website	√	√			√			
Yang et al. (2019)	BBCH65 Dataset		√						
Zhou et al. (2021)	At late vegetation, early reproductive and late reproductive growth stages of RGB and multispectral images		√			√			

(Moderate Resolution Imaging Spectroradiometer) dataset contains satellite and aerial data used in most reviewed articles for crop yield prediction. Low-resolution MODIS pixels decrease the quantity of data that needs to be processed, making the system less expensive and more efficient.

Crop Used in Yield Prediction Using Deep Learning Approaches

DL techniques are used to estimate crop yield for many different crops. The crops employed in the deep learning approaches used in the articles were analyzed and presented

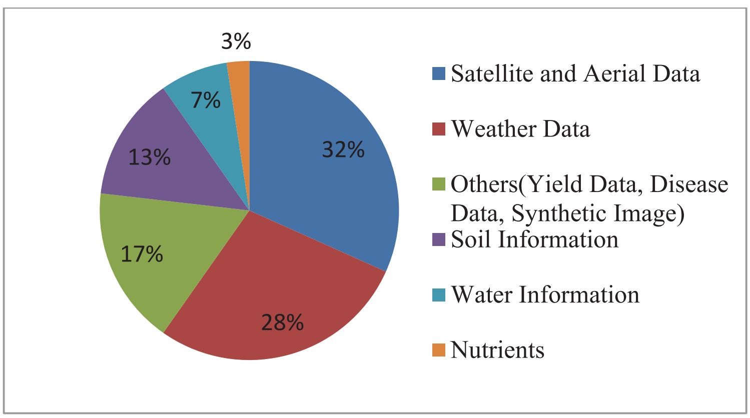

Fig. 2: Distribution of Data features group in the reviewed articles.

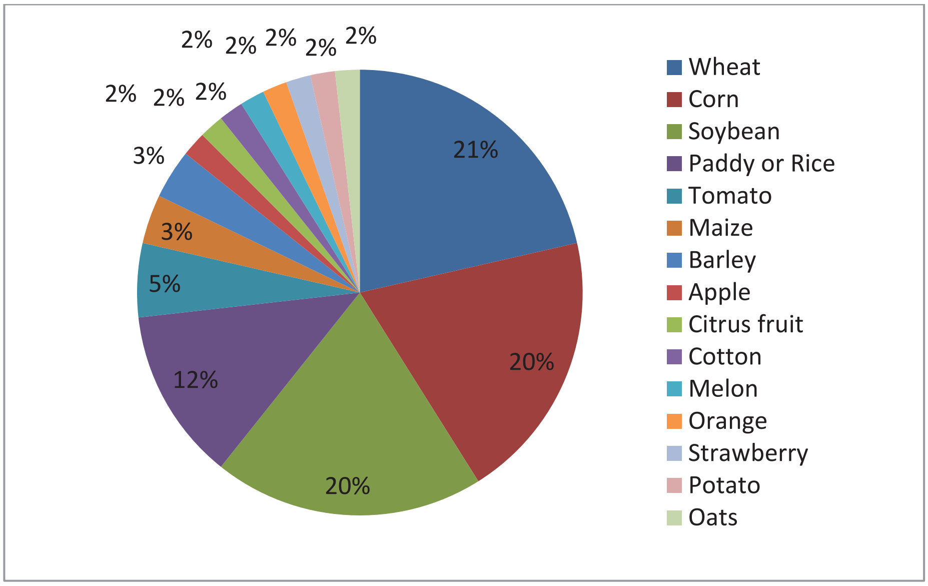

Fig. 3: Distribution of different kinds of crops used in reviewed articles.

to answer research question three (RQ3). Different crops such as Wheat, Corn, Soybean, Paddy or Rice, Tomato, Maize, Barley, Apple, Citrus fruit, Cotton, Melon, Orange, Strawberry, Potato, and Oats were investigated in the reviewed papers. The distribution of different types of crops used in the reviewed articles is displayed in Fig. 3. The yield of crops such as soybean, rice, wheat, and corn was predicted using a DL algorithm. Corn is the most common crop whose yield can be predicted widely using DL techniques.

Deep Learning Algorithms in Crop Yield Prediction

The deep learning algorithm plays a very important role in crop yield prediction. The DL approaches like CNN, RNN, LSTM, and Autoencoder were investigated in the review paper. The advantages of these algorithms were listed to answer the research question (RQ4).

Convolutional Neural Network (CNN)

A CNN is made up of many artificial neurons stacked on layers. CNN has multiple layers like the pooling layer, convolution layer, and fully connected layer (Fig. 4). The dataset is processed, and features are extracted using the Layers of CNN (Wang et al. 2020). The convolution layer uses many filters to perform the convolution operation and create a feature map. The Rectified Linear Unit layer performs the operations of a feature map on elements. The pooling layer down-samples the rectified feature map derived from the convolution layer to minimize its dimensions and smoothens the resulting two-dimensional arrays into a

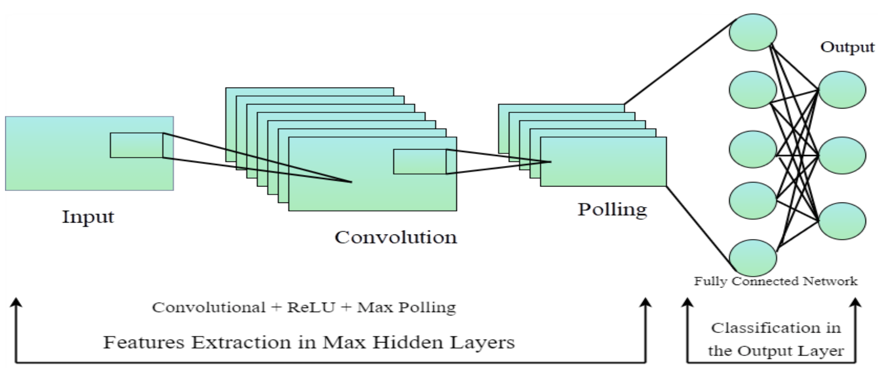

Fig. 4: Architecture of CNN.

continuous, long, single-linear vector. The fully connected layer classifies and identifies the images using the flattened matrix from the pooling layer. The filter counts, size of filters, type of padding, and stride are the design parameters for CNN. A filter is a weighted matrix to perform convolution operations on data. Padding is a technique for preserving the input dimension by adding zeroes. The stride refers to how much the filter is moved. Lenet, Alexnet, Googlenet or Inception, and VGGNet are CNN variants. CNNs are widely used for identifying satellite images, processing medical images, forecasting time series, detecting anomalies, and predicting crop yield. CNN can analyze data in various array formats, including one-dimensional, two-dimensional, and three-dimensional data. The CNN captures and explores time and spatial dependencies in weather and soil data (Wang et al. 2020). It efficiently finds salient features within data compared to traditional feedforward neural networks.

The different variants of CNN are 3D-CNN, Deep CNN, RCNN, VGGNet, and YOLO. In 3D- CNN architecture, the kernels move over three dimensions, height, length, and depth, to produce three-dimensional activation maps. In 3D CNN, convolutional layers perform 3D convolution operations (Nevavuori et al. 2020). Deep CNN is another type of CNN widely used in images and videos for pattern identification. Deep CNNs have evolved from ANN, using a three-dimensional neural pattern inspired by the visual cortex of animals. Deep CNN networks are mainly used in recommendation systems, natural language processing, image classification, and object detection. The R-CNN is a type of CNN architecture created primarily for object detection problems (Chen et al. 2019). To give a better solution to the detection problem, RCNN forms a bounding box over the object present in the image and then recognizes which object is present in the image. R-CNN has several variations, including Fast R-CNN, Mask R-CNN, and Faster R-CNN. An RPN is added to Faster R-CNN to interpret features retrieved from CNN. Researchers from the Visual Graphics Group at Oxford introduced the VGG Network.

The pyramidal structure of this network is defined by huge bottom layers closer to the images and deep top layers. It was created using a 16-layer deep CNN architecture. In the VGG, convolutional layers are followed by pooling layers. The narrowing of the layers is the responsibility of the pooling layers. It achieves its performance by using 3x3 convolutions and training on four GPUs for over two weeks. Excellent architecture for benchmarking on a specific activity and VGG pre-trained networks are frequently used for a range of applications because they are freely available on the internet are the advantages of VGG (Khaki et al. 2021b). The YOLO algorithm is used to detect objects in real-time. It divides the image into defined bounding boxes and uses a parallel recognition algorithm to determine which object class each box belongs to. After detecting these classes, it automatically merges these boxes to build an optimal bounding box around the objects. The advantages of YOLO are accuracy and speed (Lu et al. 2022).

Nevavuori et al. (2019) created a model using deep CNN to detect crop and weed, evaluate biomass, and predict wheat and barley crops yield using multispectral data. The Convolutional Neural Network algorithm produces outstanding results in object detection and image classification tasks. The results show that CNN models can estimate yields with greater accuracy when using RGB images. Nevavuori et al. (2020) discussed their research to perform intra-field yield prediction using spatial and temporal base 3D-CNN architectures with time-series and multi-temporal data. 3D CNN can be used to handle spatial and temporal data. The prediction accuracy of the 3D CNN model is high when compared to other models. Khaki et al. (2021a) created a VGG-16 model to predict the yield of corn. In addition to image classification, the VGG-16 network performs other vision tasks like object detection and counting and efficiently learns more fine-grained patterns. The model can be applied to quickly count multiple ears of corn to speed up the yield prediction. Lu et al. (2022) created a soybean yield prediction model using the YOLOv3 DL algorithm. YOLOv3 has only half of the parameters used in ResNet101, but the performance is near. The model effectively predicts the yield of the crop. Zhou et al. (2021) presented a paper that examined the possibility of using UAV multispectral imagery to estimate soybean yields from many breeding lines under drought stress using CNN. The model can accurately predict soybean yields under drought stress. Sagan et al. (2021) presented a study to create a DL-based model for field-scale yield prediction.

The model is built using DL approaches like 2-D CNN and 3-D CNN to integrate temporal, spatial, and spectral data in satellite images of the WorldView-3 and 25 PlanetScope datasets. It avoids the vanishing gradient problem by incorporating identity skip connections. Imagery deep learning-based algorithm modeling outperforms the other model. Tedesco-Oliveira et al. (2020) made a cotton yield prediction model using the CNN DL algorithm. CNN is adept in image classification and object detection. According to the testing results, the model can be used in real-time on low-cost devices. Yang et al. (2019) created an efficient CNN model for extracting key features of rice yield from low-altitude remotely sensed images. The outcomes demonstrate that the CNN model trained with RGB and multispectral datasets outperforms VI-based regression models. Khaki et al. (2021) developed a model using recurrent 3D CNN with a Transfer learning technique to predict the yield of corn and soybean. 3D-CNN captures the temporal and spatial effects in remote sensing data. Before harvest, the model can accurately estimate the yield of corn and soybean. Yang et al. (2021) designed a corn yield prediction model using the 2D-CNN DL algorithm. 2D-CNN is more suitable for classification and feature extraction. According to the findings, an integrated CNN model is better than 1D-CNN and 2D-CNN.

Mirhaji et al. (2021) developed a model using YOLOv4 to predict oranges yield. The “Bag of Freebies” and “Bag of Specials” can improve the YOLO v4 model’s efficiency and accuracy. The YOLO model is a simple and efficient method for predicting orange fruits yield. Danilevicz et al. (2021) presented a multimodal DL model using ResNet18 to estimate Maize yield. The self-attention mechanism used in ResNet aids in identifying the region’s most essential to the forecasting. The model can use as a decision-support tool. Apolo et al. (2020b) created a model using RegionCNN to estimate the yield of apples**.** The model will help to maximize production by optimizing orchard management.

Recurrent Neural Network (RNN)

RNN is derived from the feedforward network where the current step’s input depends on the previous step’s output (Chu & Yu 2020) (Fig. 5). A hidden state of an RNN preserves some information about an input sequence. So RNNs can handle any length of the input. The computation considers historical data, and the model size does not grow in proportion to the input size. RNNs are used in handwriting recognition, image captioning, natural-language processing, computer translation, crop yield prediction, and time-series analysis**.** A type of recurrent neural network called an IndRNN, widely used in crop yield prediction, has been developed to address gradient decay over layers problems, where neurons present in the same layer are independent and remain interconnected between the layers. It can be trained effectively using non-saturated activation functions like ReLu.

Chu and Yu (2020) developed a novel IndRNN-based model for accurate rice yield prediction. The IndRNN learns temporal features effectively in meteorology data. The model can predict rice yield in the summer and winter seasons.

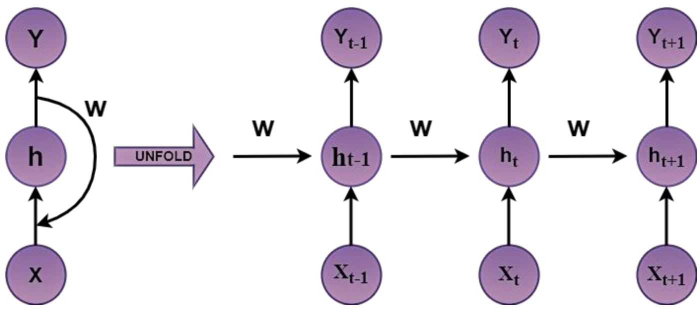

Fig. 5: Architecture of RNN.

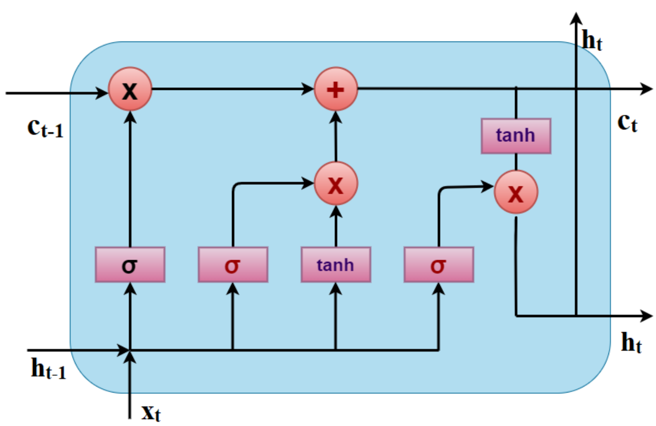

Fig. 6: Architecture of LSTM.

Long Short-Term Memory Network (LSTM)

LSTM is an RNN variant that can handle long-term dependencies and store and recall information from the past (Tian et al. 2021b). The LSTM was developed to address the drawbacks that occur during the training of traditional RNNs, such as the vanishing gradient problem and the exploding gradient problem. LSTM is effective in time-series prediction because it remembers past inputs. An LSTM unit comprises a cell (Fig. 6). An input gate, an output gate, and a forget gate are the three gates in the cell. All the gates control the data flow in the cell, and the cell stores values for an indefinite period. LSTMs are widely used in pharmaceutical growth, speech recognition, music composition, and time-series predictions. LSTM can identify the phonological characteristics and help to learn the temporal features present in the data. It has shown good ability in transfer learning and generates high accuracy yield estimation results (Wang et al. 2020).

Elavarasan and Vincent (2020) built a framework based on a deep recurrent Q-learning network using 38 features to predict the yield of crops. The Q-learning algorithm strengthens yield forecasting efficiency with the best rewards compared to other models. Tian et al. (2021a) designed a model for yield estimation in the Guanzhong Plain using an LSTM model by combining meteorological data and VTCI and LAI indices. The LSTM can detect and capture complex and nonlinear relationships in the data over long intervals. The outcomes show that the model is a robust, promising method for predicting yields. Yuanyuan Liu et al. (2022) created an LSTM-based model to forecast wheat yield across the Indo-Gangetic plains. LSTM can solve the problem in high-dimensional data and is effectively used in time-series data. With limited data, the approach can accurately predict the yield of wheat. Schwalbert et al. (2020). presented a novel LSTM-based model to estimate soybean yield in southern Brazil with four steps: data access, data wrangling, modeling, and yield prediction. The LSTM model produces better results when compared to multivariate OLS and random forest models. Shook et al. (2020) designed a framework using stacked LSTM with a temporal attention mechanism to protect crop production against climatic changes such as irregular rainfall and temperature variations. The stacked LSTM model with a temporal attention mechanism overcomes the backflow problem. Soybean yield prediction with LSTM and Temporal Attention model is reliable and accurate. Cao et al. (2021b) built a model to predict rice yield by incorporating SIF and EVI, climate variables, and soil parameters. Three models were developed using Least Absolute Shrinkage and Selection Operator regression, Random Forest, and Long Short-Term Memory Network model. The LSTM model produces accurate results when compared to Machine learning models.

Tian et al. (2021) designed a model using LSTM with an attention mechanism to forecast wheat yield with remotely sensed biophysical indices. Time-series data can be processed efficiently by LSTM, and the attention mechanism is employed to extract essential information from the input sequence data. The ALSTM (attention-based LSTM) model can give reliable crop yield estimation. Cho et al. (2021) used an attention-based LSTM network to estimate tomato yields using environmental variables. LSTM can handle long-term dependencies in data. The outcomes demonstrate that the method predicts the value more accurately. Alibabaei et al. (2021) created a bidirectional LSTM-based model to analyze time-series data in agricultural datasets to predict the yield

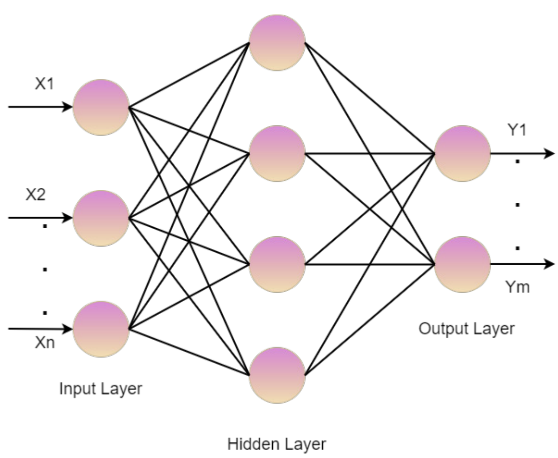

Fig. 7: Architecture of MLP.

of tomatoes and potatoes. The model accurately identifies nonlinear relationships in the data. The results demonstrate the effectiveness of the LSTM model for yield prediction. Jiang et al. (2020) created an LSTM model by integrating meteorology, remote sensing data, and crop phenology to predict the yield of corn. To avoid over-fitting, regularization techniques are used in LSTM. The model outperformed under extreme weather.

Multilayer Perceptron (MLP)

An MLP is a part of feed-forward neural networks with numerous perceptron layers and activation functions (Saravi et al. 2019) (Fig. 7). It computes the input using the weights shared by the input and hidden layers. ReLUs, tanks, and sigmoids are the activation functions that MLP uses to determine which nodes to fire (Bhojani & Bhatt 2020). It uses a training dataset to train the model to identify the correlation and learn the dependencies between the independent and target variables. It may be used to create applications for speech recognition, machine translation, image recognition, and crop yield prediction.

Saravi et al. (2019) created an agrotechnology Transfer agricultural system using the MLP deep learning algorithm, which acts as a Decision Support System to predict crop yield. Principle component analysis is added to the dataset to reduce input which speeds up the training and computing of the model. The outcomes demonstrate the MLP model is effective in predicting crop yields. Bhojani and Bhatt (2020) discussed developing a Multilayer Perceptron based model with a new activation function called DharaSig for crop yield estimation in their research. The MLP algorithm with the DharaSig activation function outperforms the original MLP algorithm for yield forecasting with a lower error rate.

Hybrid Deep Learning Approaches

Cao et al. (2021a) created a hybrid DNN+1D CNN+LSTM model for crop yield prediction. Four models were built using Convolutional Neural Networks, Random Forests, and Long Short-Term Memory networks. 1D-CNNs are used in applications like fault detection in high-power engines, structural damage detection systems, and electrocardiogram beat classification. The model can efficiently predict crop yield at field and county levels. Jeong et al. (2022) developed a model by combining LSTM and 1D-CNN to predict the yield of a rice crop. LSTM added a batch normalization layer after activation layers to speed convergence and prevent vanishing gradient problems. The approach successfully predicts the yield of rice in inaccessible locations. Lee et al. (2019) created a platform that estimates the yield of a crop by integrating crop disease data, climate change data and form status information using CNN and ANN algorithms. CNN effectively perform object detection and classification task. The model is more effective and accurate at predicting farm yields. Wang et al. (2020) built a CNN-LSTM DL model to estimate wheat yield in China's major planting area. LSTM is adept at processing time-series data in climatic data. The model has much potential for use in other varieties of crops and agricultural landscapes worldwide. Chen et al. (2019) designed a system that automatically detects strawberry flowers to predict yield using the Faster R-CNN DL algorithm. Faster R-CNN effectively handles the degradation problem using a deep residual learning framework. The model gives accurate counts of strawberry flowers and forecasts future yields. Sun et al. (2019) formed a model to predict the yield of soybeans at the country level using deep CNN and LSTM.

CNN explores spatial features, and LSTM reveals phenological properties of the MODIS dataset. The outcomes reveal the CNN-LSTM model is efficient in soybean yield prediction. Khaki and Archontoulis (2020) presented a paper to accurately predict the yield of corn and soybean using CNN and RNN with a back propagation method. RNN, with the backpropagation method, supports time-dependent data, and CNN captures the temporal and spatial dependency in the dataset. The dataset contained four different types of dataset: weather, yield performance, management-related information, and soil. The CNN-RNN model gives better prediction results when compared to other models. Qiao et al. (2021) designed a novel spatial-spectral-temporal neural network using recurrent 3D-CNN to predict the yield of wheat and corn. 3D-CNN exploits spectral information from 3D data. The model outperforms better prediction performance when compared to other models. Apolo et al. (2020a) designed a model to identify and estimate the yield and size of citrus fruits using Faster R-CNN + LSTM. The Faster-R-CNN model can utilize Inception, Atrous, and ResNet architectures to improve accuracy and efficiency. The results show that the model can estimate the yield of all types of fruit. Shahhosseini et al. (2021) created a model by combining CNN and DNN DL algorithms to predict the yield of corn. CNN captures the temporal and spatial dependencies in data. The model was designed to predict corn yield and assist agronomic decision-makers.

RESULTS AND DISCUSSION

Performance Evaluation Metrics

Different evaluation metrics utilized to measure the performance of DL in crop yield prediction are given in Table 2. A total of 18 different evaluation metrics such as RMSE, R2, MAE, MAPE, MSE, F1 Score, Recall, MedAE, mAP, Accuracy, Average Precision, Kappa coefficient,

Table 2: Performance metrics used in crop yield prediction.

Performance Metrics	Formula	Description
Root Mean Square Error (RMSE)	$RMSE = \sqrt{\frac{1}{n}\sum_{j=1}^{n}(y_j - \hat{y}_j)^2}$	y_j – Actual value $\hat{y}_j$ - Forecast value n - no. of observation
Mean Square Error (MSE)	$MSE = \frac{1}{n}\sum_{j=1}^{n}(y_j - \hat{y}_j)^2$	
Mean Absolute Error (MAE)	$MAE = \frac{1}{n}\sum_{j=1}^{n} \vert y_j - \hat{y}_j \vert$	
Mean Absolute Percentage Error (MAPE)	$MAPE = \frac{1}{n}\sum_{j=1}^{n} \vert \frac{y_j - \hat{y}_j}{y_j} \vert$	
Coefficient of determination (R^2)	$R^2 = 1 - \frac{RSS}{TSS}$	*RSS* –Sum of square of residuals *TSS* – Total sum of square
Precision	$P = \frac{TP}{TP + FP}$	*TP* – True positive *FP* – False positive
Recall	$R = \frac{TP}{TP + FN}$	*TP* – True positive *FN* – False negative
F1 Score	$F1 = 2 * \frac{precision * recall}{precision + recall}$	

Table 3: Overview of different deep learning algorithms, crop utilized, and evaluation metrics used in crop yield prediction.

Authors	Deep Learning Algorithms	Crops	Performance Evaluation Metrics
Alibabaei et al. (2021)	Bidirectional LSTM	Tomato, Potato	MSE, R^2
Apolo et al. (2020b)	R-CNN	Apple	R^2, MAE, RMSE
Apolo et al. (2020)	Faster R-CNN +LSTM	Citrus fruit	Precision, Recall, F1 Score
Bhojani and Bhatt (2020)	MLP	Wheat	MAE, RMSE, MAPE, MSE, RAE, RRSE
Bi and Hu (2021)	Genetic algorithm-assisted DNN	Crop	RMSE
Cao et al. (2021a)	DNN+1D CNN+LSTM	Wheat	RMSE, R^2
Cao et al. (2021b)	LSTM	Rice	RMSE, R^2
Chen et al. (2019)	Faster R-CNN	Strawberry	Mean Average Precision
Cho et al. (2021)	Attention-based LSTM +ARMA	Tomato	MSE, RMSE
Chu and Yu (2020)	IndRNN	Rice	MAE, RMSE
Danilevicz et al. (2021)	Spectral deep neural network (ResNet18)	Maize	RMSE, relative RMSE, R^2 score
Elavarasan and Vincent (2020)	Deep RNN +Q Learning	Paddy	MAE, MSE, RMSE, R^2, MedAE, MAPE
Elavarasan and Vincent (2021)	DBN+FNN	Paddy	MSLE, RMSE, MSE, MAE, R^2, MedAE, MSLE
Gao et al. (2020)	DNN	Corn and Soybean	R^2, MAE, MAPE
Jeong et al. (2022).	LSTM+1D-CNN	Rice	R^2, RMSE, NSE
Jiang et al. (2020)	LSTM	Corn	RMSE, R^2
Kalantar et al. (2020)	RetinaNet deep CNN, Transfer learning	Melon	Average precision score, F1 score, MAPE.
Khaki and Archontoulis (2020)	CNN-RNN	Corn	RMSE

Authors	Deep Learning Algorithms	Crops	Performance Evaluation Metrics
Khaki and Wang (2019)	DNN	Maize	RMSE
Khaki et al. (2021a)	CNN with Transfer Learning	Corn and Soybean	MAE
Khaki et al. (2021b)	VGG-16	Corn	MAE, RMSE
Liu et al. (2022)	LSTM	Wheat	R^2, RMSE
Lu et al. (2022)	YOLOv3+RCNN+SSD+FPN	Soybean	Accuracy, Precision, Recall, F1 value, MAP
Ma et al. (2021)	Bayesian Neural Network	Corn	R^2, RMSE, MAPE
Maimaitijiang et al. (2020).	DNN	Soybean	R^2, RMSE
Mirhaji et al. (2021)	YOLO-V4	Orange	MAP, Precision, F1-score, Recall
Moghimi et al. (2020)	MLP	Wheat	RMSE, R^2
Nevavuori et al. (2019)	Deep CNN	Wheat and barley	MAE, MAPE
Nevavuori et al. (2020)	3D CNN	Wheat, Barley, Oats	MAE, MAPE
Qiao et al. (2021)	Recurrent 3D-CNN	Wheat and Corn	RMSE, R^2, MAPE
Sagan et al. (2021)	ResNet-18	Soybean, Corn	R^2, RMSE
Saravi et al. (2019)	MLP	Maize	RMSE
Schwalbert et al. (2020)	LSTM	Soybean	MAE, MSE, RMSE
Shahhosseini et al. (2021)	CNN-DNN	Corn	RMSE, RMSE
Shook et al. (2020)	LSTM and Temporal Attention	Soybean	RMSE
Sun et al. (2019)	Deep CNN+LSTM	Soybean	RMSE, R^2
Teodoro et al. (2021)	DL Model	Soybean	MAE, RMSE, Pearson's correlation coefficient
Tian et al. (2020)	BPNN with PSO algorithm	Wheat	R^2
Tian et al. (2021a)	LSTM with an attention mechanism	Wheat	R^2, MAPE, RMSE, NRMSE
Tian et al. (2021b).	LSTM	Wheat	R^2, RMSE
Wang et al. (2020).	LSTM+CNN	Wheat	R^2, RMSE
Yang et al. (2019)	Deep CNN	Rice	RMSE, R^2, MAPE
Yang et al. (2021)	2D- CNN	Corn	Kappa coefficient, Accuracy
Zhou et al. (2021)	CNN	Soybean	RMSE

MSLE, RAE, RRSE, NSE, Precision, and Relative RMSE were investigated in the reviewed papers. The DL algorithms and different evaluation approaches used in the articles were analyzed and presented in Table 3 to answer the research question (RQ5)

CONCLUSION

The paper analyzes the study of a deep learning algorithm based on crop yield prediction. The survey categorizes existing strategies based on the crop used, the methodologies employed, the datasets used, and the performance metrics used. CNN, RNN, LSTM, and MLP are some of the DL algorithms used to predict crop yield. The CNN algorithm produces outstanding results in object detection and image classification tasks. The LSTM can detect and capture complex and nonlinear relationships in the data over long intervals. Two main DL algorithms for accurately estimating crop yields are CNN and LSTM. These techniques can successfully estimate and forecast various crops' yields. Transfer learning and Data augmentation were used to solve the large dataset training in DL models. The RMSE was the most frequently used evaluation metric in the reviewed articles, followed by MAPE, R^2, MSE, and MAE. In the future, the factors like plant disease, temperature and rainfall, pests, fertilizer, and soil quality can be considered for improving the performance of crop yield prediction using DL approaches.

REFERENCES

Abbas, F., Afzaal, H., Farooque, A.A. and Tang, S. 2020. Crop yield prediction through proximal sensing and machine learning algorithms. Agronomy, 10(7): 1046.

Alibabaei, K., Gaspar, P.D. and Lima, T.M. 2021. Crop yield estimation using deep learning based on climate big data and irrigation scheduling. Energies, 14(11): 3004.

Apolo, O.E.A., Guanter, J.M., Cegarra, G.E., Raja, P. and Ruiz, M.P. 2020. Deep learning techniques for estimation of the yield and size of citrus fruits using a UAV. Europ. J. Agron., 115(4): 183-194.

Apolo, O.E.A., Ruiz, M.P., Guanter, J.M. and Valente, J. 2020a. A cloud-based environment for generating yield estimation maps from apple orchards using UAV imagery and a deep learning technique. Front. Plant Sci., 1086.

Bhojani, S.H. and Bhatt, N. 2020. Wheat crop yield prediction using new activation functions in neural network. Neural Comp. Appl., 5: 1-11.

Bi, L. and Hu, G. 2021. A genetic algorithm-assisted deep learning approach for crop yield prediction. Soft Comp., 25(16): 10617-10628.

Cao, J., Zhang, Z., Luo, Y., Zhang, L., Zhang, J., Li, Z. and Tao, F. 2021a. Wheat yield predictions at a county and field scale with deep learning, machine learning, and the google earth engine. European J. Agron., 123: 126204.

Cao, J., Zhang, Z., Tao, F., Zhang, L., Luo, Y., Zhang, J. and Xie, J. 2021b. Integrating multi-source data for rice yield prediction across china using machine learning and deep learning approaches. Agric. Forest Meteorol., 297: 108275.

Chen, Y., Lee, W.S., Gan, H., Peres, N., Fraisse, C., Zhang, Y. and He, Y. 2019. Strawberry yield prediction based on a deep neural network using high-resolution aerial orthoimages. Remote Sens., 11(13): 1584.

Cho, W., Kim, S., Na, M. and Na, I. 2021. Forecasting of tomato yields using attention-based LSTM network and ARMA model. Electronics, 10(13): 1576.

Chu, Z. and Yu, J. 2020. An end-to-end model for rice yield prediction using deep learning fusion. Comp. Electr. Agric., 174, 105471.

Danilevicz, M.F., Bayer, P.E., Boussaid, F., Bennamoun, M. and Edwards, D. 2021. Maize yield prediction at an early developmental stage using multispectral images and genotype data for preliminary hybrid selection. Remote Sens., 13(19): 3976.

Elavarasan, D. and Vincent, P.D. 2020. Crop yield prediction using deep reinforcement learning model for sustainable agrarian applications. IEEE Access, 8: 86886-86901.

Elavarasan, D. and Vincent, P.D. 2021. Fuzzy deep learning-based crop yield prediction model for sustainable agronomical frameworks. Neural Comp. Appl., 33(20): 13205-13224.

Gao, Y., Wang, S., Guan, K., Wolanin, A., You, L., Ju, W. and Zhang, Y. 2020. The ability of sun-induced chlorophyll fluorescence from OCO-2 and MODIS-EVI to monitor spatial variations of soybean and maize yields in the Midwestern USA. Remote Sens., 12(7): 1111.

Jeong, S., Ko, J. and Yeom, J.M. 2022. Predicting rice yield at pixel scale through synthetic use of crop and deep learning models with satellite data in South and North Korea. Sci. Tot. Environ., 802: 149726.

Jiang, H., Hu, H., Zhong, R., Xu, J., Xu, J., Huang, J. and Lin, T. 2020. A deep learning approach to conflating heterogeneous geospatial data for corn yield estimation: A case study of the US Corn Belt at the county level. Glob. Change Biol., 26(3): 1754-1766.

Kalantar, A., Edan, Y., Gur, A. and Klapp, I. 2020. A deep learning system for single and overall weight estimation of melons using unmanned aerial vehicle images. Comp. Electr. Agric., 178, 105748.

Khaki, S. & Archontoulis, S.V. 2020. A CNN-RNN framework for crop yield prediction. Front. Plant Sci., 10: 1750.

Khaki, S. and Wang, L. 2019. Crop yield prediction using deep neural networks. Front. Plant Sci., 10: 621.

Khaki, S., Pham, H. and Wang, L. 2021a. Simultaneous corn and soybean yield prediction from remote sensing data using deep transfer learning. Sci. Rep., 11(1): 1-14.

Khaki, S., Pham, H., Han, Y., Kuhl, A., Kent, W. and Wang, L. 2021b. Deepcorn: A semi-supervised deep learning method for high-throughput image-based corn kernel counting and yield estimation. Knowl. Based Syst., 218: 106874.

Lee, S., Jeong, Y., Son, S. and Lee, B. 2019. A self-predictable crop yield platform (SCYP) based on crop diseases using deep learning. Sustainability, 11(13): 3637.

Liu, Y., Wang, S., Wang, X., Chen, B., Chen, J., Wang, J. and Zhu, K. 2022. Exploring the superiority of solar-induced chlorophyll fluorescence data in predicting wheat yield using machine learning and deep learning methods. Comp. Electr. Agric., 192: 106612.

Lu, W., Du, R., Niu, P., Xing, G., Luo, H., Deng, Y. and Shu, L. 2022. Soybean yield preharvest prediction based on bean pods and leaves image recognition using deep learning neural network combined with GRNN. Front. Plant Sci., 12: 791256.

Ma, Y., Zhang, Z., Kang, Y. and Özdoğan, M. 2021. Corn yield prediction and uncertainty analysis based on remotely sensed variables using a Bayesian neural network approach. Remote Sens. Environ., 259: 112408.

Maimaitijiang, M., Sagan, V., Sidike, P., Hartling, S., Esposito, F. and Fritschi, F.B. 2020. Soybean yield prediction from UAV using multimodal data fusion and deep learning. Remote Sens. Environ., 237: 111599.

Mirhaji, H., Soleymani, M., Asakereh, A. and Mehdizadeh, S.A. 2021. Fruit detection and load estimation of an orange orchard using the YOLO models through simple approaches in different imaging and illumination conditions. Comp. Electr. Agric., 191: 106533.

Moghimi, A., Yang, C. and Anderson, J.A. 2020. Aerial hyperspectral imagery and deep neural networks for high-throughput yield phenotyping in wheat. Comp. Electr. Agric., 172: 105299.

Muruganantham, P., Wibowo, S., Grandhi, S., Samrat, N.H. and Islam, N. 2022. A systematic literature review on crop yield prediction with deep learning and remote sensing. Remote Sens., 14(9): 1990.

Nevavuori, P., Narra, N. and Lipping, T. 2019. Crop yield prediction with deep convolutional neural networks. Comp. Electr. Agric., 163: 104859.

Nevavuori, P., Narra, N., Linna, P. and Lipping, T. 2020. Crop yield prediction using multitemporal UAV data and spatio-temporal deep learning models. Remote Sens., 12(23): 4000.

Paudel, D., Boogaard, H., de Wit, A., Janssen, S., Osinga, S., Pylianidis, C. and Athanasiadis, I N. 2021. Machine learning for large-scale crop yield forecasting. Agric. Syst., 187: 103016.

Petersen, L.K. 2018. Real-time prediction of crop yields from MODIS relative vegetation health: A continent-wide analysis of Africa. Remote Sens., 10(11): 1726.

Qiao, M., He, X., Cheng, X., Li, P., Luo, H., Zhang, L. and Tian, Z. 2021. Crop yield prediction from multi-spectral, multi-temporal remotely sensed imagery using recurrent 3D convolutional neural networks. Int. J. Appl. Earth Observ. Geoinform., 102: 102436.

Rahnemoonfar, M. and Sheppard, C. 2017. Deep count: fruit counting based on deep simulated learning. Sensors, 17(4): 905.

Rashid, M., Bari, B.S., Yusup, Y., Kamaruddin, M.A. and Khan, N. 2021. A comprehensive review of crop yield prediction using machine learning approaches with special emphasis on palm oil yield prediction. IEEE Access, 9: 63406-63439.

Sagan, V., Maimaitijiang, M., Bhadra, S., Maimaitiyiming, M., Brown, D.R., Sidike, P. and Fritschi, F.B. 2021. Field-scale crop yield prediction using multi-temporal WorldView-3 and PlanetScope satellite data and deep learning. ISPRS J. Photogramm. Remote Sens., 174: 265-281.

Saravi, B., Nejadhashemi, A.P. and Tang, B. 2019. Quantitative model of irrigation effect on maize yield by the deep neural network. Neural Comp. Appl., 7:-14.

Schwalbert, R.A., Amado, T., Corassa, G., Pott, L.P., Prasad, P.V. and Ciampitti, I.A. 2020. Satellite-based soybean yield forecast: Integrating machine learning and weather data for improving crop yield prediction in southern Brazil. Agric. Forest Meteor., 284: 107886.

Shahhosseini, M., Hu, G., Khaki, S. and Archontoulis, S.V. 2021. Corn yield prediction with ensemble CNN-DNN. Frontiers in Plant Science, 12.

Shook, J., Gangopadhyay, T., Wu, L., Ganapathysubramanian, B., Sarkar, S. and Singh, A.K. 2020. Crop yield prediction integrating genotype and weather variables using deep learning. ArXiv 6: 13847.

Sun, J., Di, L., Sun, Z., Shen, Y. and Lai, Z. 2019. County-level soybean yield prediction using deep CNN-LSTM model. Sensors, 19(20): 4363.

Tedesco-Oliveira, D., da Silva, R.P., Maldonado, W. and Zerbato, C. 2020. Convolutional neural networks in predicting cotton yield from images of commercial fields. Comp. Electr. Agric., 171: 105307.

Teodoro, P.E., Teodoro, L.P.R., Baio, F.H.R., da Silva Junior, C.A., dos Santos, R.G., Ramos, A.P.M. and Shiratsuchi, L.S. 2021. Predicting days to maturity, plant height, and grain yield in soybean: a machine and deep learning approach using multispectral data. Remote Sens., 13(22): 4632.

Tian, H., Wang, P., Tansey, K., Han, D., Zhang, J., Zhang, S. and Li, H. 2021a. A deep learning framework under attention mechanism for wheat yield estimation using remotely sensed indices in the Guanzhong Plain, PR China. Int. J. Appl. Earth Observ. Geoinform., 102: 102375.

Tian, H., Wang, P., Tansey, K., Zhang, J., Zhang, S. and Li, H. 2021b. An LSTM neural network for improving wheat yield estimates by integrating remote sensing data and meteorological data in the Guanzhong Plain, PR China. Agric. Forest Meteor., 310: 108629.

Tian, H., Wang, P., Tansey, K., Zhang, S., Zhang, J. and Li, H. 2020. An IPSO-BP neural network for estimating wheat yield using two remotely sensed variables in the Guanzhong Plain, PR China. Comp. Electr. Agric., 169: 105180.

Van Klompenburg, T., Kassahun, A. and Catal, C. 2020. Crop yield prediction using machine learning: A systematic literature review. Comp. Electr. Agric., 177: 105709.

Wang, X., Huang, J., Feng, Q. and Yin, D. 2020. Winter wheat yield prediction at the county level and uncertainty analysis in main Wheat-Producing regions of China with deep learning approaches. Remote Sens., 12(11): 1744.

Wolanin, A., Mateo-García, G., Camps-Valls, G., Gómez-Chova, L., Meroni, M., Duveiller, G. and Guanter, L. 2020. Estimating and understanding crop yields with explainable deep learning in the Indian Wheat Belt. Environ. Res. Lett., 15(2): 024019.

Yang, Q., Shi, L., Han, J., Zha, Y. and Zhu, P. 2019. Deep convolutional neural networks for rice grain yield estimation at the ripening stage using UAV-based remotely sensed images. Field Crops Res., 235: 142-153.

Yang, W., Nigon, T., Hao, Z., Paiao, G.D., Fernández, F.G., Mulla, D. and Yang, C. 2021. Estimation of corn yield based on hyperspectral imagery and convolutional neural network. Comp. Electr. Agric., 184: 106092.

Zhou, J., Zhou, J., Ye, H., Ali, M.L., Chen, P. and Nguyen, H.T. 2021. Yield estimation of soybean breeding lines under drought stress using unmanned aerial vehicle-based imagery and convolutional neural network. Biosyst. Eng., 204: 90-103.