An Extensive Survey of Deep learning-based Crop Yield Prediction Models for Precision Agriculture

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Abstract

Precision agriculture, as the trademark of the agriculture 4.0 period, has assured to reform agricultural practices using monitoring and intervention technologies to increase productivity and decrease the environmental impact. Computer vision (CV) and deep learning (DL) models are commonly used as key enablers for precision agriculture. CV technologies utilize digital images for the interpretation and understanding of the world to offer precise, region orient details about the crops and respective surroundings. Today, CV has been widely employed to support precision agriculture processes like crop yield prediction (CYP), crop monitoring, weed control, plant disease detection, weed detection, etc. CYP is a significant process for decision making at the national and regional levels. Several machine learning (ML) and DL based models have been presented for accurate CYP. Therefore, this paper reviews existing DL-based CYP models developed for precision agriculture. In this view, the major aim of the review is to identify, group, and discuss the existing intelligent agriculture approaches. The existing methods are surveyed based on the underlying techniques, objectives, dataset used, and available datasets. The outcome of the survey pointed out the significance of applying DL models for CYP in precision agriculture.

Keywords: Precision agriculture, Computer vision, Deep learning, crop yield prediction, Image processing

1. Introduction

Crop yield is one of the significant parts of agriculture and has several links with the human community. Yield prediction is highly a difficult process in precision agriculture, which is essential for crop market planning, harvest management, crop insurance, and yield mapping. The crop yield is influenced by several aspects like management practice, crop genotype, and environments [1]. The crop genotype has been enhanced dramatically for many years by seed companies. Environments which are varying temporally and spatially, contain large effects on location to location and year to year differences in crop yield. In these environments, precise yield prediction is more useful for worldwide food production. Import and export decisions in time could be carried out depending upon precise yield prediction. Farmers can make use of the yield prediction for creating financial decisions and knowledgeable management. The efficiency of hybrid crops is predicted in novel and untested positions. But effective crop yield prediction (CYP) is extremely complex because of several composite aspects. For instance, genotype and environmental aspects frequently have interaction with one another that creates yield prediction a difficult process.

Environmental aspects like weather factors frequently contain composite non-linear effects that are complex for precise estimation. Policy makers based on the precise prediction for making import and export decisions reinforce the national food security. Seed companies require predicting the efficiency of novel hybrids in several atmospheres to breed for enhanced varieties. Farmers and Growers also assist from yield prediction for making financial decisions and informed management. The effect of the genetic marker should be calculated so that it can be subjected to interaction with many fields of management practice and environmental conditions. Several researches have been concentrated on describing the phenotype (like yield) as an environment (E), interaction (G×E), and their explicit function of genotype (G). The most common and direct technique is to assume the additive impacts of E and G and process their interaction as noise [2]. A widespread method for studying the G×E effects is to recognize the interaction and effects of huge environment instead of additional detailed environmental elements. Various researches have been presented for clustering the environment depending upon discovered driver of G×E interactions utilized the location regression and the transferred multiplicative method for G×E interactions analyses by separating environment to equivalent sets.

Burgueño et al. [3] presented a combined method of factor analytic (FA) and linear mixed method for clustering environment and genotype and identify their interaction. They stated that FA method could enhance the prediction up to 6% while they exit complex G×E patterns in the information. The linear mixed methods have been utilized for the investigation of both interactive and additive impacts of separate genetics and environments. In recent years, machine learning (ML) methods are employed for CYP, involving association rule mining, decision tree, multivariate regression, and artificial neural network (ANN) [4]. An essential characteristic of ML technique is that they process the outcome (i.e. crop yield) as an implied function of the input parameter (environmental and genes elements) that can be a higher complex and nonlinear function.

In recent times, Deep learning (DL) methods have been utilized for CYP. Compared to general ML models that have single hidden layer, DL techniques with many hidden layers determine better performance [5]. But the deeper methods are very complex for training process and need more advanced hardware and optimization methods. DL is an extended version of ML, which adds more depth to the models and transforms the data utilizing several functions which enable hierarchical data representation by different stages of abstraction. Feature learning, i.e., automated extraction of features from the input data is the major advantage of the DL models [6-9]. IT can resolve complex problems effectively and quickly enabling high parallelization. The complex models applied in DL result in increased classifier accuracy and reduced error in the regression problem, providing large databases. The DL model comprises distinct elements such as convolution, pooling, fully connected (FC), activation functions, etc.

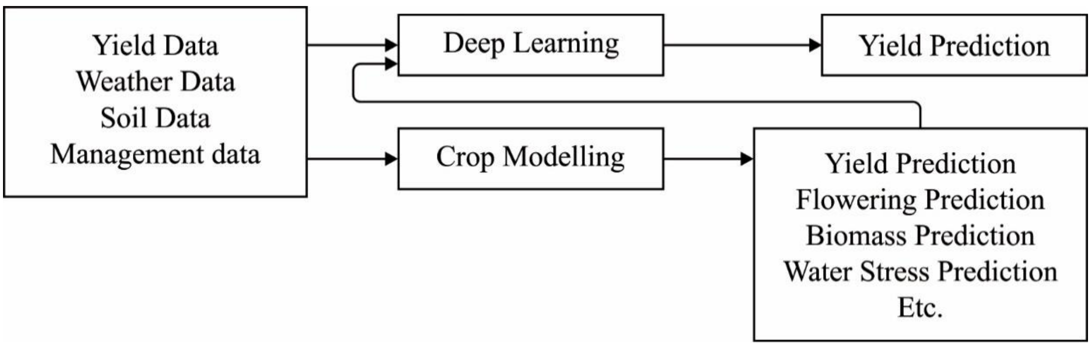

Fig. 1. Process involved in DL based precision agriculture

The hierarchical model and high learning ability of the DL model enable to carry out classification and prediction process. It exhibits flexibility and adaptability to several highly complex issues. Several DL models have been existed in the earlier studies for precision agriculture. An overview of the processes involved in the DL based precision agriculture is given in Fig. 1. [6] utilized DL methods like convolution neural networks (CNNs) and recurrent neural networks (RNNs) for predicting soybeans yield in the United States depending upon a series of remote sensor images are captured beforehand the harvest. This method exceeds conventional remote sensing-based methods by 15% based on Mean Absolute Percentage Error (MAPE). [7] utilized CNN for CYP depending upon remote sensing images. This technique utilized 3D convolution for including the spatio-temporal feature, and exceed other ML techniques [8].

Since several CYP models are available in the literature, there is a need to review the existing DL based yield prediction models. With this motivation, this survey intends to investigate the works related to the domains of DL and CYP. The existing methods are surveyed based on the underlying techniques, objectives, dataset used, and available datasets. For getting the insights, existing works have been investigated under different aspects. Here, a set of 4 research questions (RQ) have been stated as follows.

- RQ1- What are the DL models that have been utilized in the existing works of CYP?
- RQ2- What are all the features utilized for CYP by the use of DL models?
- RQ3- What are performance measures and validation models that have been available in the previous works for CYP?
- RQ4- What are challenging issues exist in the area of CYP by DL models?

2. Review of Existing DL based Crop Yield Prediction Models

Elavarasan and Vincent [10] developed a new Deep Recurrent Q-Network mod for predicting crop yield. The presented technique includes an RNN model over the Q-Learning RL technique. The serially stacked layers of RNN are used along with the Q- learning network designed a crop yield forecasting. The linear map mapped into the RNN outcome to the Q-values. At last, the agent gets an aggregated value for the actions carried out by the minimization of error and maximization of predictive accuracy. Khaki et al. [11] presented a new CNN with RNN model, called CNN-RNN to forecast the crop yield depending upon the ecological data and management practices. The presented CNN-RNN technique with random forest (RF), FC neural network (FCNN), and LASSO is employed for corn and soybean forecast in the US. The presented model can be integrated into the backpropagation technique, which revealed the weather condition, weather predictive accuracy, soil condition, and management practice.

Khaki and Wang [12] developed a new DNN model for the prediction of hybrid corn yield. The DNN model involves a feature selection problem to decrease the dimensionality of the input space with no considerable reduction in the predictive accuracy. An effective dimension decreasing approach: Self Organizing Map (SOM) is presented together with Latent Dirichlet Allocation (LDA) in [13]. The SOM approach is the most appropriate dimension decreasing approach for highlighting the self-arranging outline. Later decreasing the measurement, the dimension decreased data are utilized for predicting weather for a satisfactory result. A satisfactory period for a proper crop is ordered with the guideline of DNN classification method. Wang et al. [14] display possible outcomes in forecasting soybean crop yields in Argentina by utilizing DL methods. It also attains reasonable outcomes with a transfer learning method for predicting Brazil soybeans harvest with a small quantity of data. The stimulating for transfer learning is that the achievement of DL method is mainly based on rich ground truth trained data.

You et al. [15] presented an inexpensive, scalable, and accurate technique for CYP utilizing open access remote sensing data. Initially, it declines handcrafted traditional feature, which is utilized in the remote sensing community and introduce a method depending upon the latest illustration of learning concepts. It also establishes a novel dimension reducing method permits for training a Long Short Term Memory (LSTM) or CNN and automatically learn beneficial feature while labeled trained information is insufficient. Lastly, it integrates a Gaussian Process component for explicit method of spatio temporal patterns of the data and additionally enhances the accurateness. In Nevavuori et al. [16], CNN–DL method shows an extraordinary efficiency in image classification process – are employed for building a method to CYP depending upon RGB and NDVI information's are attained from UAV. The impact on several factors of CNNs like tuning of the hyper variable, regularization strategy, network depth, and selection of the training method on the predictive performance is confirmed. The aim of [17] is to calculate the energy of UAV based multi-modal data fusion by utilizing multispectral, thermal sensor, and RGB for estimating soybeans (i.e., Glycine max) grain yield with the DNN architecture. The thermal images, RGB, and multispectral have been gathered by utilizing low-cost multi sensor UAV from a testing location in Missouri, USA, and Columbia. Multimodal information's, like structure, texture feature, thermal and canopy spectral, was combined and extracted for predicting crop grain yield by utilizing different techniques.

Schwalbert et al. [18] proposed a new method for performing in season ("near real-time") soybean yield predictions in southern Brazil by LSTM, NN, weather data, and satellite imagery. The aims of this research are to (i) relate the efficiency of 3 distinct methods like LSTM-NN, RF, and multi-variate OLS linear regression to predict soybean yield by utilizing land surface temperature EVI, NDVI, and rainfall as autonomous parameters, and (ii) calculate earlier (at the time of soybean developing period) for predicting yield with moderate accuracy. Khaki et al. [19] presented a novel method is known as YieldNet that uses a new DL architecture which utilizes the transfer learning among soybean and corn yield predictions by allocating the weights of the backbone feature extraction. Furthermore, to assume the multi-target response parameter, it developed a novel loss function. Mathematical outcomes determine that this presented technique precisely predicts the yield from 1 to 4 months earlier the harvest, and is inexpensive for other advanced methods.

Chu and Yu [20], proposed a new end-to-end predictive method that combines 2 backpropagation neural networks (BPNN) with an independently RNN (IndRNN), called BBI method, which is presented for addressing these problems. In initial phase, BBI method preprocesses the meteorology data and original area. In next phase, the IndRNN and BPNN are utilized for learning deep temporal and spatial features in similar manner. In 3rd phase, additional BPNN integrates 2 types of deep feature and learn the relations among this rice yields and deep features for making prediction for winter and summer rice yields.

Wang et al. [21], introduced a 2 branch DL method for predicting winter wheat yield in the major cultivating areas of China at the county level. The initial branch of the method was made depending upon LSTM network with inputs from meteorological and remote sensing data. Additional branch was made by utilizing CNN for modeling static soil features. The method was trained after by utilizing the detrended statistical yield data from 1982 to 2015 and calculated by leave one year out validation. Nevavuori et al. [22] presented the possibility of spatio temporal DL framework in crop yield time series demonstrating and predictive with RGB time sequence data. By utilizing LSTM and CNN networks as temporal and spatial base frameworks, they trained and developed convolutional LSTM, 3D CNN, and CNN LSTM frameworks with full 15-week image frame series from the complete developing period of 2018.

Jiang et al. [23], introduced an LSTM method, which combines meteorology, heterogeneous crop phenology, and remote sensing data for estimating county level corn yields. By combining meteorological indices and heterogeneous phenology based remote sensing, the LSTM method calculates for 76% of yield variances over the Corn Belt, enhanced from 39% of yield variances described by phenology based meteorological indices. Cao et al. [24], proposed the main winter wheat production areas of China as instance, it is related to conventional ML technique RF and 3 DL methods, like LSTM, 1D-CNN, and DNN for predicting crop yield by combining public access data with the GEE (Google Earth Engine) platform, involving satellite, climate, spatial information, and soil properties. Yue et al. [25] presented a data driven encoder-decoder method, by LSTM and convolutional LSTM that is employed for predicting cumulative precipitation, daily sunshine duration, and average temperature for the future. For testing the efficiency of the convolutional LSTM based method, in both conventional LSTM and CNN LSTM encoder-decoder methods are compared.

Table 1 Comparison of different DL based CYP models

References	Year	Objective	Technique used	Crop Type	Performance Measures
[10]	2020	Develop a DRL technique for CYP	Deep Recurrent Q-Network	Paddy	MAE, MSE, RMSE, accuracy
[11]	2020	Design a CNN-RNN model for corn and soyabean CYP	CNN-RNN	corn and soybean	MSE, RMSE, accuracy
[12]	2019	Propose a DL based CYP model	DNN	Corn	RMSE, accuracy
[13]	2018	Design a weather and CYP technique	Weighted SOM+DNN	kharif and ragi crops	Sensitivity, specificity, accuracy
[14]	2018	Employ DTL model for CYP using remote sensed data	LSTM	soybean	RMSE
[15]	2017	Design an inexpensive DL based CYP using remote sensed data	CNN-LSTM	soybean	MAE, MAPE
[16]	2019	Introduce a DL model for CYP using NDVI and RGB data from UAV	DCNN	wheat and malting barley	MAE, MAPE

[17]	2020	Design a UAV based CYP model using DL and multimodal fusion techniques	DNN, fusion model	soybean	RMSE, accuracy
[18]	2020	Present a DL based CYP model using satellite and weather data.	LSTM	soybean	MAE
[19]	2020	Develop a CYP model for multiple crops concurrently	CNN	Corn, soybean	MAE
[20]	2020	Introduce a DL based fusion model for CYP	BPNN, IndRNN	Rice	MAE, RMSE
[21]	2020	Employ a DL model for winter yield prediction	LSTM, CNN	Wheat	Accuracy
[22]	2020	Present a CYP model using Multitemporal UAV Data and Spatio-Temporal	3D-CNN, LSTM	Nine crops (varieties of wheat, barley, and oats)	MAPE, MAE
[23]	2019	Design a DL based CYP model to conflating heterogeneous geospatial data	LSTM	Corn	RMSE
[24]	2021	Introduce a scalable and easy model for accurate CYP	DNN, LSTM	Corn	RMSE, accuracy

[25]	2020	Analyze the growth levels of crops using DL model	LSTM, ConvLSTM	Maize	MAE, RMSE, accuracy
[26]	2020	Design an ensemble model with hyperspectral images for CYP	Ensemble model	Corn	Scatter plots
[27]	2021	Present a semi-supervised DL model for CYP	DeepCorn	Corn	
[28]	2020	Introduce a DL based CYP using UAV images	Improved LSTM	Cotton	MSE, RMSE

Feng et al. [26], carried out an in season alfalfa yield prediction by UAV based hyper spectral images. In particular, it initially extracts a huge amount of hyper spectral indices from the original data and accomplished a feature selection for reducing the data dimension. Later, an ensemble ML method was established by integrating 3 broadly utilized base learners comprise of SVR, K-nearest neighbors (KNN), and RF. This method efficiency was calculated over the research field in Wisconsin.

Khaki et al. [27], presented a new DL technique to count on ear corn kernel in field for collecting real-time information and eventually, enhance problem solving for yield maximization. This DeepCorn approach illustrates that this architecture is powerful in several situations. The DeepCorn calculates the amount of corn kernel in an image of corn ear and predicts the kernel counts depending upon the evaluated density map. DeepCorn utilizes a truncated VGG-16 as a backbone for feature extraction and combines feature mapping from several scales of the network for making it strong towards image scale variation. It accepts a semi-supervised learning method for improving the efficiency of the presented approach. Table 1 shows the comparison of distinct DL based crop yields prediction models.

Wang et al. [28] are presented for predicting the cotton yield by an enhanced LSTM method that is an artificial RNN framework utilized in the area of DL. The LSTM method has feedback links and integration of distinct gates like forget gate, output gate, and input gate for controlling the required data from storage for prior time stamp information and upgraded from this time stamp inputs. In this research, a UAV imaging system comprising multi spectral camera of 5 narrow spectral bands of near infrared (840±20 nm), red (668±5 nm), green (560±10 nm), red edge (717±5 nm) and blue (475±10 nm), is utilized for collecting imagery data of cotton in 3 crucial development phases. The imagery data have been preprocessed for removing calibrate reflectance, background, and registered to produce information based geo referenced data. Multivariable aspects of GNDVI, NDVI, canopy temperature, and size have been extracted from UAV multi spectral images and utilizes as input for the LSTM method. The variables of the LSTM method should be optimum to enhance the efficiency for precise yield calculation.

3. Results and Discussion

This section validates the performance analysis of different CYP models such as deep reinforcement learning (DRL), ANN, gradient boosting (GB), RF, and other DL based algorithms like Bernoulli Deep Belief Network (BDN), Bayesian Artificial Neural Networks (BAN), Rough Auto Encoders (RAE) and Interval Deep Generative Artificial Neural Networks (IDANN) interms of accuracy and MAPE.

Table 2 Comparative Analysis of Various Models in terms of Accuracy and MAPE

Models	**Accuracy (%)**	**MAPE (%)**
DRL	93.70	17.00
BDN	92.10	20.00
BAN	91.70	27.00
IDANN	91.00	29.00
RAE	90.70	32.00
DL	91.85	28.00
ANN	90.50	38.00
RF	70.70	53.00
GB	81.20	41.00
SOM-KNN	58.99	-
WSOM-KNN	81.23	-
DCNN	-	08.80

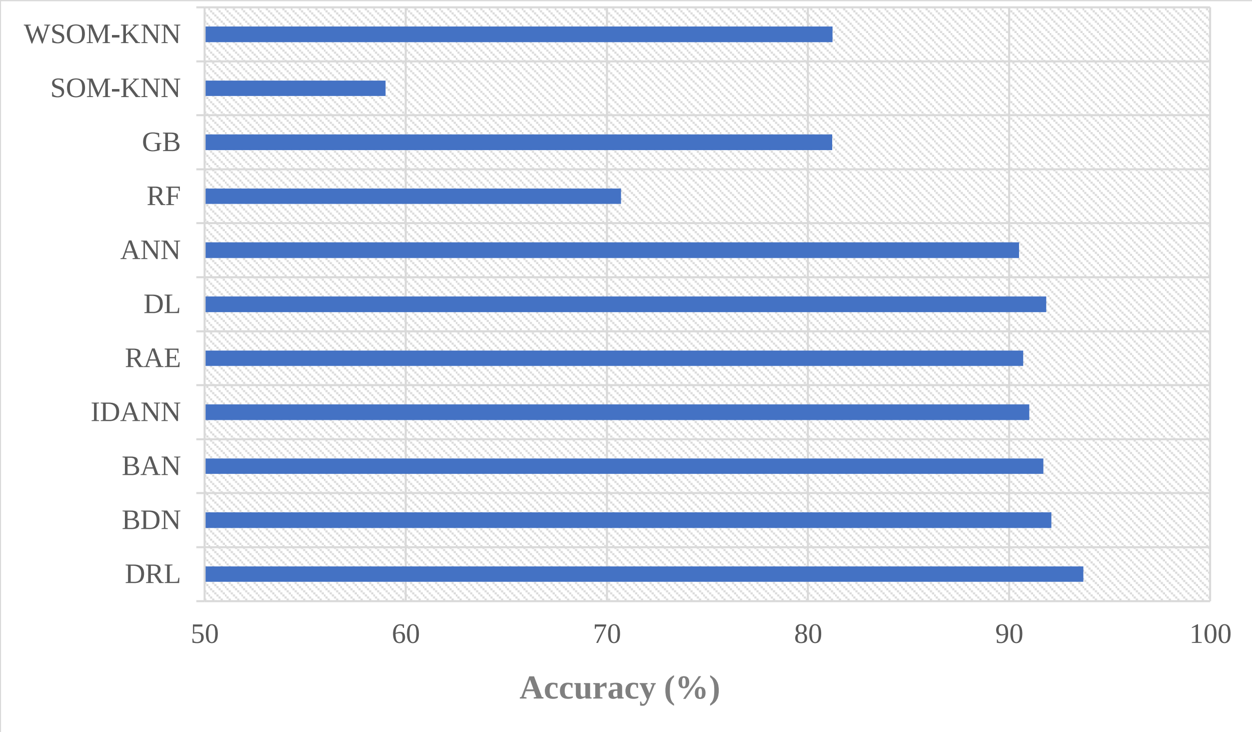

Fig. 2. Accuracy analysis of different CYP models

Table 2 demonstrates the comparative study of reviewed CYP models. Fig. 2 investigates the results analysis of different CYP models interms of accuracy. From the figure, it is evident that the SOM-KNN model has accomplished poor results with an accuracy of 58.99%. At the same time, the RF, GB, and WSOM-KNN models have obtained slightly increased performance by offering an accuracy of 70.7%, 81.2%, and 81.23% respectively. Simultaneously, the ANN and RAE models have reached moderate results with the accuracy of 90.5% and 90.7% respectively. Concurrently, the IDANN, BAN, and DL models have accomplished reasonable accuracy of 91%, 91.7%, and 91.85% respectively. Though the BDN model has appeared as a near optimal performer with an accuracy of 92.1%, the presented DRL model has offered effective performance with an accuracy of 93.7%.

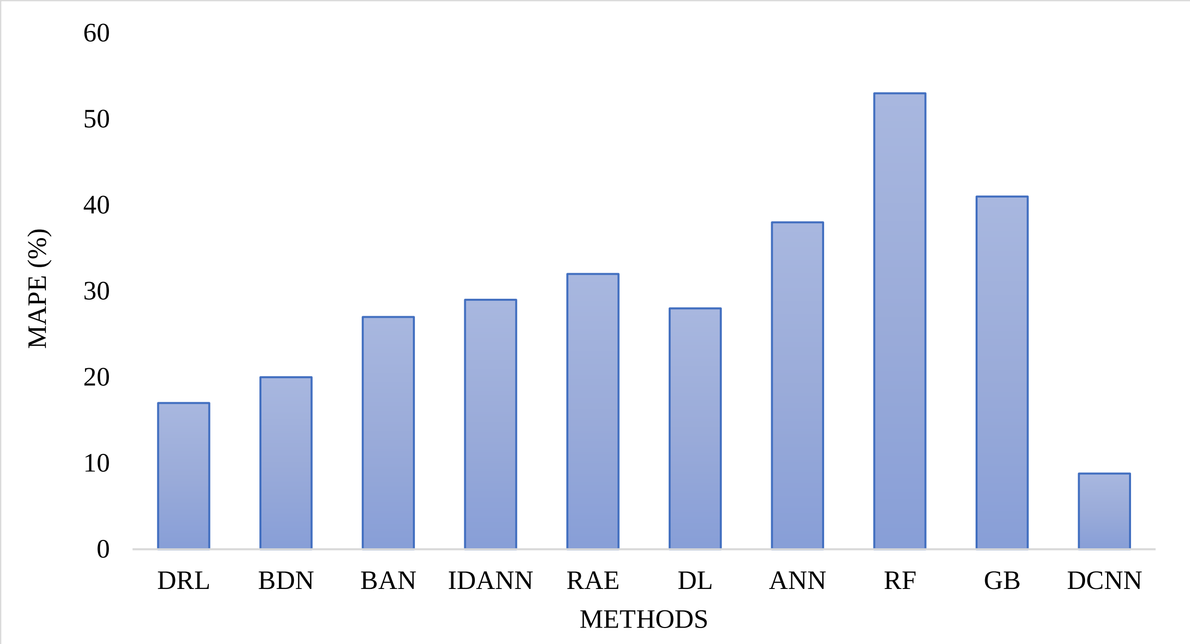

Fig. 3. MAPE analysis of different CYP models

Fig. 3 examines the results analysis of different CYP models with respect to MAPE. From the figure, it is clear that the DCNN model has accomplished worse results with the MAPE of 8.8%. In line with, the DRL, BDN, and BAN techniques have achieved somewhat higher performance by offering a MAPE of 17%, 20%, and 27% correspondingly. Concurrently, the DL and IDANN approaches have attained moderate outcomes with the MAPE of 28% and 29% correspondingly. Followed by, the RAE and ANN techniques have accomplished reasonable MAPE of 32%, and 38% respectively. But the GB model has appeared as a near better performer with the MAPE of 41%, the RF technique has offered effective performance with a MAPE of 53%.

4. Conclusion

This survey has aimed to investigate the works related to the domains of DL and CYP in precision agriculture. This study aims to perform a review to identify, group, and discuss the existing intelligent agriculture approaches. The existing methods are surveyed based on the underlying techniques, objectives, dataset used, and available datasets. The outcome of the survey pointed out the significance of applying DL models for CYP in precision agriculture. For getting the insights, existing works have been investigated under different aspects. The outcome of the survey pointed out the significance of applying DL models for CYP in precision agriculture. A detailed results analysis was also performed to highlight the particular characteristics of the reviewed models and a brief comparative study is also made. As a part of future scope, an advanced DL with metaheuristic optimization algorithm based CYP models will be designed.

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