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Advanced crop yield prediction using machine learning and deep learning: a comprehensive review

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ABSTRACT

The advancement of machine learning (ML) and deep learning (DL) techniques has significantly improved crop yield prediction, making it more accurate and reliable. In this review, the implementation of ML and DL algorithms for crop yield prediction is thoroughly investigated, focusing on their crucial role in enhancing crop productivity. Along with ML and DL algorithms examine, the review analyses the use of remote sensing technologies, such as satellite and drone data, in providing high-resolution inputs essential for accurate yield predictions. The study identifies the state of art algorithms, most used features, data sources and evaluation metrics, providing a comparison of ML and DL. The findings indicate that DL models are more effective with large datasets, while ML models remain robust for smaller datasets. The future directions are proposed to develop the generalised models for different crops and regions. The review aims to assist researchers by summarising state of art techniques and identifying the present.

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1. INTRODUCTION

The field of computer science is constantly advancing and ever-evolving, driven by the pursuit of even more sophisticated solutions to complex problems. Machine learning (ML) has emerged as a powerful paradigm within this domain, enabling computers to learn and adapt without explicit programming [1]. ML encompasses a diverse set of techniques, each with its unique strengths and applications [2]. Some common approaches include supervised learning, which involves training algorithms on labelled data to perform tasks like classification and regression. Unsupervised learning, on the other hand, focuses on uncovering hidden structures within unlabelled data, allowing for tasks like data clustering and dimensionality reduction. Additionally, reinforcement learning enables systems to learn through trial and error, interacting with an environment.

ML is also making significant contribution in the agriculture industry, particularly in the area of crop yield prediction [3]. ML can help farmers and policymakers mitigate food insecurities. It is based on the concept of statistics and ML in which crop yield is predicted using historical data associated with the crops like climate, soil, and region. Modern tools such as satellites, drones and sensors are also used to obtain data and monitor crops. One of the key drivers of this progress is the integration of remote sensing technology [4]. Satellites and drones equipped with various sensors can gather data on factors like soil moisture, vegetation health, and weather patterns from a distance [5]. These models then identify intricate relationships between these diverse factors and historical crop yields, allowing for accurate predictions.

With surge in demand of food with increasing population, ML in agriculture has propelled to the forefront of research aimed at advancing the sector. However, navigating the complexities of choosing suitable datasets, algorithms, and methodologies can be challenging for researchers as these vary greatly depending on the area of study and type of crop. This review paper addresses questions such as the most used features, data sources, types of evaluation metrics, the algorithms and models used and the type of remote sensing techniques used in recent studies. Our review addresses these gaps by comparing and summarizing the most recent advances based on the literature available to answer our prepared research question that aims to create a more generalised approach for researchers that can be used for most crops and areas. The aim is to equip researchers with the insights needed to make informed decisions by answering the following questions:
RQ1: what are the state-of-the-art techniques used?
RQ2: which among ML and deep learning (DL) is better for making yield predictions?
RQ3: what are matrices used for model evaluation?
RQ4: what are the data sources?
RQ5: what are the most used features?
RQ6: which among ensembled models and traditional ML and DL perform better?
RQ7: what are the limitations and future directions?

Similar reviews are conducted by researchers but each vary with one another based on the type of crop or area being studied. It is crucial to analyse the recent reviews to get insights on the recent practices in crop yield prediction. According to the study [6] which was carried out on different crops, geographical positions and various features. It was found that DL performs better than ML for making predictions of which convolutional neural network (CNN) and long short-term memory (LSTM)-based models were identified to be most effective. It was also concluded that meteorological data and Vegetation are the most used features. Similarly, the review [7] also included papers that conducted studies performed in different environments stated that there were no single or multiple specific models found that were able to outperform others and also stated that including more features in the dataset doesn’t necessarily mean that they perform better. However, it concluded that there were a few popular models that are used very often such as random forest, neural network, linear regression, and gradient boosting tree. Further, the review concluded that out of the neural network, the most used models were CNN, LSTM, and deep neural network (DNN).

According to the study [8] which was conducted on Palm oil prediction stated that while there was no particular algorithm that could be concluded as the best but few most promising ML algorithms were linear regression, random forest and neural network. Out of the DL algorithms, the popular algorithms were DNN, CNN, and LSTM. The review also concluded that there are very few studies on Palm oil with versatile features which makes it difficult to determine which algorithm or features are best since it’s still in the early stages. According to another review with emphasis specifically on DL algorithms for yield prediction [9]. Crop yield with DL depends majorly on the type of data and crops. It was also noted that image was the most demanded source of data with the majority of publications focusing on supervised learning. CNN was widely used for making predictions which also outperformed other DL algorithms such as DNN, LSTM, Faster R-CNN and hybrid models. The most used evaluation metric was root mean square error (RMSE) followed by R^2, mean absolute percentage error (MAPE), mean absolute error (MAE), and mean square error (MSE). Similarly [10] also concluded that DL provides a promising solution for crop yield estimation. However, they are largely depend on many factors including scalability, availability of the dataset, and location of study. We still are very far from finding a generalised approach to predict crop yield in all types of environments. Our study aims at finding the most relevant and common features for crop yield prediction in various environments with state of the art techniques and data sources to give a better and cleared idea to researchers to start with crop yield prediction with the updated techniques that can be be applied over most crops and environments. Table 1 summarizes the gaps in the considered studies for comparison without study. ‘Y’ represents YES and ‘N’ represents NO.

Table 1. Test model specifications and test conditions

Comparison points	[6]	[7]	[8]	[9]	[10]	Our review
State of the art techniques discussed	Y	Y	Y	Y	N	Y
Comparison between ML and DL	N	N	N	N	N	Y
Evaluation metric	N	Y	N	Y	N	Y
Data sources	N	N	N	Y	N	Y
Ensembled vs classic ML, DL models	N	N	N	N	N	Y
Most used features	N	Y	Y	Y	Y	Y
Limitations and future work	Y	Y	Y	Y	N	Y

2. METHOD

This review addresses unanswered questions outlined in Table 1 and updates the existing literature with the latest findings. It examines the comparison between ensemble and traditional ML/DL models, as well as between ML and DL models specifically for crop yield prediction, areas not clearly covered in previous reviews. By synthesizing recent findings, this review provides researchers with updated insights into best practices, data sources, and methodologies in the field. This contribution aims to support researchers in building upon current work and advancing future research in crop yield prediction.

2.1. Literature review

A detailed systematic review is carried out in this study to answer our specific research questions. This includes the selection criteria of all the literature included and reviewed in this study. The selection of all the literature was done using a bunch of relevant keywords for our study. The literature included in this review were pulled from Google Scholar in a year-wise manner. The keywords used are mentioned in Table 2. The yearly filter was used on Google Scholar to download papers that were of relevance. After this, each paper was reviewed for relevance based on the abstract, introduction and technologies used. The papers further discarded were due to the reasons that they were associated with plant disease detection, traditional phenology without using ML or DL, specific to data mining, internet of thing (IoT) and soil management. Finally, we were left with 80 quality literature to review in this study which was included.

Table 2. The keywords used to search papers

Sr. No.	Keywords
1	Crop yield prediction
2	Crop yield prediction ML
3	Crop yield prediction DL
4	Crop yield prediction DL remote sensing
5	Crop yield prediction ML remote sensing

More precisely as shown in Figure 1, the total number of downloaded papers was 238. From the downloaded papers 198 papers were selected based on the title and further 165 papers were selected from the then selected papers based on the abstract of the paper. Among the 165 papers finally 80 papers were selected that are used for our study. The Figure 1 gives an insight on the selection criteria.

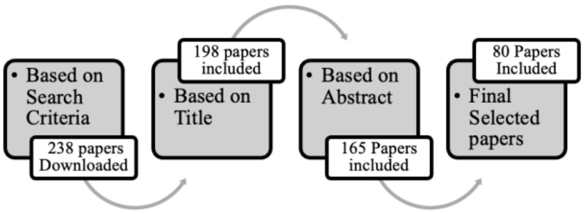

Figure 1. Paper selection criteria

As shown in Figure 2 the selected papers range from the year 2014 to 2024. The increment in the papers can be seen from 2019. The researcher's interest in the domain has grown with the advancement in satellite technology and enhanced computation.

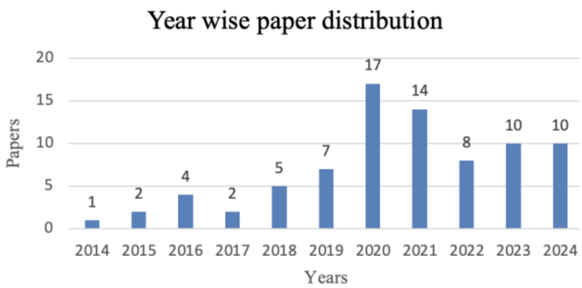

Figure 2. Year wise paper distribution

2.2. Algorithms

There are several algorithms available for making crop yield prediction, and the selection of most suitable one depends on multiple factors, including the type of data available, the number of features in the dataset, and the nature of the data—whether it is statistical, image-based, or a combination of both. Additionally, understanding the linearity or non-linearity of the data plays a crucial role in determining which algorithm will perform best. Crop yield prediction is a complex issue involving various factors such as climate conditions, soil properties, rainfall, temperature, humidity, fertilizer usage, and crop variety. The accuracy of predictions depends on selecting an appropriate ML or DL model that can effectively capture the relationships between these factors.

2.2.1. Support vector machines

These algorithms find a hyperplane in the feature space that best separates the data points belonging to different classes. Support vector machine (SVM) focus on identifying a small subset of training data points (support vectors) that define the hyperplane's margins. This approach makes them robust to outliers and efficient for high-dimensional data. SVM has given promising results in many studies such as this study [11] that predicts potato yield using Sentinel 2 data in Segovia, Spain with a high r^2 value of 0.93. Another study [12] conducted in Tamil Nadu, India, compared different feature subsets for crop yield prediction and also showed that SVM had a high R Score of 0.92. A research work [13] which also used Landsat-8 data showed that SVM had achieved a high accuracy of 98.72%. A recent study [14] aimed at comparing various ML models for Soybean yield prediction using remote sensing and weather data also showed that SVM had a decent R^2 score of 0.722. A study [15] was each on the prediction of Winter Wheat on multi-sourced data in China and also showed that SVM was among one of the highest accurate algorithms for making predictions. This being said SVM though not the best in all cases gives promising results because of its inability to handle non linear and very large datasets. SVM is also computationally very expensive.

2.2.2. Random forests

It is build upon decision trees by creating an ensemble of them. Each tree is trained on a random subset of features and data points, enhancing accuracy and reducing overfitting. Predictions from all trees are then aggregated for a final output. A study [16] done on soybean and corn datasets 4 times a year for 3 years as test data concluded that random forest gives good accuracy with RMSE observed 5.62 bushels per acre for the soybean dataset for August 2017. Similarly, another research [17] that was done in the main wheat-producing region of China using data from various sources such as remote sensing meteorological data etc also received the second highest R^2 score among all algorithms studied. The r^2 of random forest was 0.72. A study [18] performed on wheat crops aimed to compare random forest and three different DL algorithms and concluded that random forest had the best R^2 score of 0.89. Another research [14] also conducted on soybeans also concluded that random forest after tuning its hyperparameters specifically gave a promising and the highest R^2 of 0.748 in the particular study outperforming support vector regression (SVR). Another study [15] that was done to predict winter wheat yield concluded that random forest demonstrates the best generalization ability among other popular algorithms used. Also, according to Sarr and Sultan [19] random forest performed the best in predicting Maize yield with an R^2 value of 0.64. The study also had peanut, millet and sorghum datasets in which random forest also performed well and was behind by a small margin.

2.2.3. Artificial neural networks

They consist of interconnected layers of processing units (neurons) that learn patterns from data through an iterative process called backpropagation. Strengths include tackling complex, non-linear problems and excelling at feature extraction. According to a study [20] potato yield in Bangladesh using remote sensing satellites using artificial neural network (ANN) and the error of prediction was very small and less than 10%. Which indicated that ANN is highly accurate in predicting potato yield in Bangladesh. The study [21] which was done on Rice crops in the Indian region found that the accuracy of ANN was 97.5 in this study with a sensitivity of 96.3. Another research [19] was performed in Senegal located in the African continent and statistical and satellite data were used ANN outperformed all other models in predicting Peanut and Sorghum yield with an R^2 score of 0.66 and 0.57 respectively. Similarly [22] was carried to predict Mustard crop yield which concluded that ANN had an accuracy of 99.94%, precision of 99.94% and an F-Score of 0.9976. Another study [12] which was executed to predict paddy crops in the state of Tamil Nadu in India which achieved an R^2 score of 0.92 for ANN. Similarly [23] aiming to predict rice produced a high testing R^2 score of 0.978.

2.2.4. Extreme gradient boosting

It leverages ensemble learning with gradient boosting. New models are sequentially added to correct the errors of previous models, focusing on minimising the loss function while controlling model complexity to prevent overfitting. According to research [24] extreme gradient boosting (XGBoost) was the best-performing algorithm for crop prediction with the highest R^2 score of 84.79, which outperformed all other algorithms in the study. The highest R^2 score by XGBoost was 0.92 in the month of April 2022. A study [25] aimed at predicting maize yield and Nitrogen loss from soil using data from seven locations in the US Midwest over 5-7 years and concluded that XGBoost had 3rd highest R^2 score among all algorithms used in the study. However, XGBoost had the highest R-RMSE in predicting N-Loss at 98.3%. Similarly [26] aimed at predicting crop yield using meteorological data and remote sensing data from moderate resolution imaging spectroradiometer (MODIS) and it was concluded that XGBoost had the best accuracy in the study with an R^2 score of 0.845. However, a research [27] aimed at predicting corn yield in USA county-wise from the year 2000-2018 XGBoost did not perform well as it had one of the highest RMSE scores among all the algorithms used. Similarly [28] was conducted on nine features from remote sensing satellites and ML algorithms were applied month wise out of which XGBoost's performance was not outstanding with very high R^2.

2.2.5. Long short-term memory

It is a specific type of recurrent neural network (RNN), that excels at handling sequential data (time series) by learning long-term dependencies. LSTMs utilize memory cells with gates to control information flow, allowing the network to retain relevant information for extended periods. A study [29] was aimed at predicting winter wheat yield used a Bayesian optimization-based LSTM model which concluded that the proposed model performed the best compared to all other models in the study with a R^2 score of 0.82. Another study [30] performed over the region of Punjab, India to predict wheat crops showed that RNN with LSTM outperformed all other algorithms in the study by a considerable margin. Similarly, the study [31] was executed over a dataset consisting of meteorological data and soil and crop data and compared different models in the study. LSTM performed the best among all other models with a marginal difference with an accuracy of 86% in predicting yield. Another study [32] also showed that Stacked LSTM performed the best out of all algorithms considered for the study with weather variables and had an R^2 score of ~0.732. This shows that LSTM can produce promising results for crop yield prediction.

2.2.6. Convolutional neural networks

CNNs are specialized ANN architectures designed for processing grid-like data, particularly images. CNNs efficiently extract spatial features through convolutional layers with learnable filters and pooling layers for dimensionality reduction. A research [33] aimed to make crop yield prediction using CNN-RNN performed well outperforming all other algorithms used in the study. Similarly, another study [34] aimed at predicting soybean yields also showed CNN performed well when combined with LSTM the CNN-LSTM model produced the best RMSE compared to all other models in the study. Another study [35] aimed at predicting crop yield using satellite images in the US showed that the CNN-LSTM model had an R^2 score of 0.91. Similarly [36] authors also showed that CNN+RNN+2FFNN produced the highest correlation coefficient 0.9183. This shows that if the right data is obtained CNN in combination with other networks can be very accurate in predicting crop yield.

3. EVALUATION METRICS

3.1. Regression metrics

Regression is a supervised ML technique that is used to predict continuous values. It plots a best-fit line passing through the data. Crop yield prediction is typically a regression task, where models predict continuous values (yield in tons per hectare). No model is perfect and there is always a scope of some error. Regression metrics help in evaluating the models. Here are the key metrics for evaluating regression models: RMSE measures the average difference between predicted and actual yield values. Lower RMSE indicates better model performance. MAE calculates the average absolute difference between predicted and actual yield values. R-squared (R^2) metric represents the proportion of variance in the actual yield data explained by the model's predictions. A value closer to 1 indicates a better fit.

3.2. Classification metrics

Classification tasks are also part of supervised ML and are typically used for categorising data by predicting its correct label. In some cases, models might predict yield categories (low, medium, high) instead of continuous values. Here are the relevant evaluation metrics used to evaluate classification algorithms: Accuracy metric simply measures the percentage of correctly classified yield categories. F1-score metric considers both precision (proportion of true positives among predicted positives) and recall (proportion of true positives identified by the model). An F1-score closer to 1 indicates better model performance, especially for imbalanced datasets where some yield categories might be less frequent. Among the 80 papers considered in our review four classification metrics were used F-Score, recall, precision, accuracy a total 20 times and regression metrics were used 135 times in total which consisted of MSE, RMSE, MAE, R^2, MAPE, relative root mean squared error (RRMSE), and R Score.

4. RESULTS AND DISCUSSION

For the present review, we have considered both conference and journal articles to ensure a comprehensive analysis of the existing literature. To maintain the quality and relevance of the review, we applied a rigorous inclusion and exclusion criteria, based on parameters such as relevance of studies to the theme, and alignment with the objectives of our study. We have finalised 67 journal articles and 13 articles from conferences i.e., 84% from journals and 16% from conferences as represented in Figure 3.

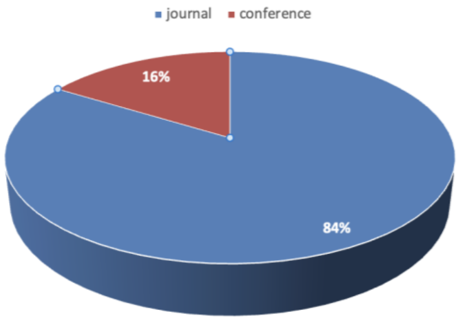

Figure 3. Journal vs conference papers

4.1. Research questions

4.1.1. RQ1: what are the state-of-the-art techniques used?

State-of-the-art techniques can be judged based on the most used techniques in recent publications and the techniques or models that tend to perform the best in various studies to predict crop yield production. In the study [37] concluded that random forest regressor outperformed all other supervised learning models included in the study. Another study [38] that was done on Soyabean crop concluded that the best-performing model was RNN in the study. A similar study [39] showed the reliability of making significant predictions. The study [31] also compared various models and concluded that LSTM outperformed all other models in the study. Another study [40] used an optimised LSTM approach to receive a high accuracy in prediction. The study [41] carried in region of China on winter wheat also showed that LSTM performed the best among all other models included in the study. The researchers [29] that used Bassein optimizer with LSTM performed the best among all models. Considering the discussed studies and other detailed studies that we compared in this review, we can infer that state of art algorithms used are ensembled tree models like decision tree, random forest, XGBoost and LSTM, RNN, and CNN are also used that usually tend to perform better compared to the classic ML models.

Figure 4 shows the number of times these algorithms were used in all the considered studies. random forest emerged as the most frequently employed algorithm across 34 studies. Following closely behind were SVM, ANN, LSTM, least absolute shrinkage and selection operator (LASSO), decision tree regression, linear regression, CNN, and gradient boosting regression, with usage counts of 20, 16, 14, 14, 13, 13, 10, and 10 studies, respectively. The diversity of algorithms indicates the variety of tasks performed in the research. The others in the below figure consisted of Bayesian Ridge, R-CNN, ACNN-BDLSTM, light use efficiency (LUE), bayesian ridge (BR), Huberg regression, long short-term memory-Gaussian process (LSTM-GP), wavelet convolutional neural network (W-CNN), radial basis function neural network (RBF-NN), cat boost regression, Res-NET 2D, 3D, ABR, DCNN, multiple logistic regression, temporal convolutional neural network (TCNN), CNN-RNN, convolutional neural network-Gaussian process (CNN-GP), multi-view gated Fusion (MVGF), and adaptive boosting (ADA Boost) each being used a single time in our selected papers and collective count being 19.

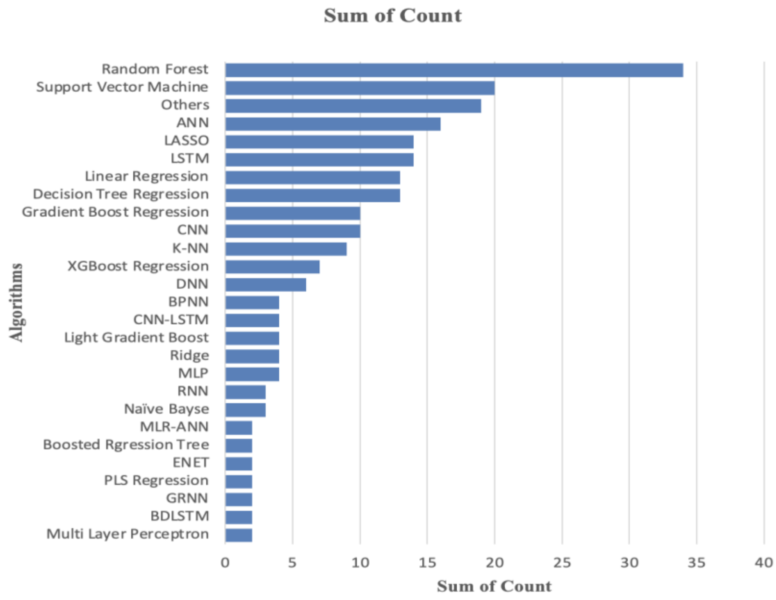

Figure 4. Count of algorithms

4.1.2. RQ2: which among machine learning and deep learning is better for making yield predictions?

A study [42] that compared SVR, partial least squares (PLS) regression, random forest regression (RFR) and DNN showed that DNN outperformed all other models in the study. Another study [38] done on soybean crop compared various ML and DL models such as ADA Boost, DNN, least absolute shrinkage and selection operator, random forest, and SVM out of which DNN outperformed all the models. The study [43] which included DNN compared various models out of which SVR and KNN outperformed all other models. This happened due to the small dataset used to train the model since DNN is more sensitive to the amount of data fed into it. A similar study [41] which included LASSO, random forest, and LSTM concluded that LSTM performed the best among all studied models in predicting winter wheat yield in China. The study [18] that compared DL models such as DNN, CNN, LSTM, and random forest showed that DNN performed best among the compared models. The research work [44] showed that XGBoost performed better than CNN and LSTM due to small dataset again showing that DL models require a large dataset. Another study [30] conducted over the region of Punjab, India on Wheat crop compared RNN and LSTM with ANN, random forest and multivariate Linear regression. RNN and LSTM outperformed the classical ML algorithms with a large margin. Another study [32] that also showed that stacked LSTM outperformed other ML models included in the study such as LASSO and SVR. Another study [36] that used ensembled DL models also showed that CNN-RNN+ 2Feed forward neural network outperformed linear regression, XGBoost, random forest with considerable difference in testing accuracy. While it can be said that there is no definitive answer as to which ML performs best. It can be concluded from the present literature that the performance of the models majorly depends on the dataset that is being used and more over the size of dataset. In general when there is large dataset available DL algorithms tend to perform better and when there is comparatively a smaller dataset ML tend to perform better for making crop yield predictions.

4.1.3. RQ3: what are matrices used for model evaluation?

Evaluation metrics are an important aspect of any study as these serve as the parameters for evaluating how well a model performs. The selection of evaluation metrics depends on the objective of the study however, the few most used metrics for crop yield prediction are RMSE, R^2, and MAE. These are used mostly in regression tasks. While RMSE is good to compare models on the same dataset this is not the perfect parameter to compare models trained on different datasets as RMSE can vary and doesn't have a fixed range. For comparison of models from different studies, R^2 value is used because the value ranges from 0 to 1, 1 being a perfect model. Studies often use more than one evaluation metric for model evaluation to give a better idea for comparison such as [45] comparing 4 models on all three parameters to predict the yield. Authors have similarly [18] made use of R^2 and RMSE to evaluate predictions made on wheat crops. The Figure 5 shows the frequency of evaluation metrics used in the paper. The RMSE is the most used evaluation metric followed by R^2 and MAE.

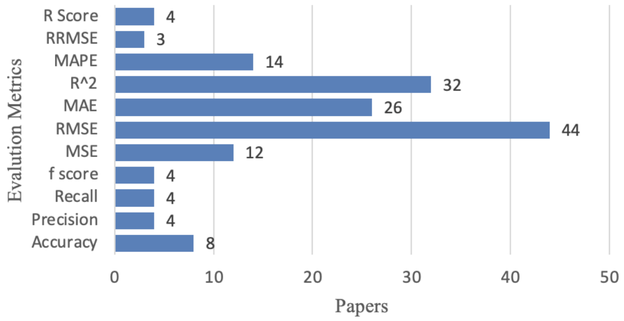

Figure 5. Evaluation metrics used in papers

4.1.4. RQ4: what are the data sources?

Data sources primarily depend upon the region of study and the type of crop being studied. Crop largely depends upon meteorological data such as rainfall, temperature, and humidity. National Oceanic and Atmospheric Administration (NOAA) which is a part of the U.S. Department of Commerce stores a wide range of meteorological datasets majorly from the U.S. Territories and waters. Studies such as [20], [46] conducted over the U.S make use of this service. Similar to NOAA countries have their own datacentre to monitor and collect data for research such as the study [47] conducted on Columbia used a dataset obtained from the Consultation and Download of Hydrometeorological Data system of the Institute of Hydrology, Meteorology and Environmental Study of Columbia, Ministry of Agricultural and Rural Development. Another study [48] conducted over Tamil Nadu, India used the Department of Economics and Statistics, Government of Tamil Nadu. Similar studies [49], [50] also used Indian government sources to obtain data. The yield data of crop particularly is obtained from the United States Department of Agriculture such as in the studies [34], [51]-[56].

Remote sensing data is actively used to monitor crops. Among our selected studies satellite data was the major source of remote sensing data with some studies also using unmanned aerial vehicle (UAV). For the satellites, MODIS was used majorly for the calculation of Vegetation Indices in 58% of the studies such as [14], [19], [26], [35], [44], [51], [57]-[61]. Followed by Landsat 8 satellite used in the studies [13], [57], [62], [63] and Landsat 7 used in the studies [35], [62]. This was followed by the use of other satellites such as Sentinel 2 [23], [35], [52], [57], [62], Sentinel 2B and Sentinel 2B [64], World View-3 and UAV [42], Landsat 2, Landsat 2 (L2A) [65], and Sentinel 2L1C [11]. The Figure 6 represents the satellite sources used in the studies.

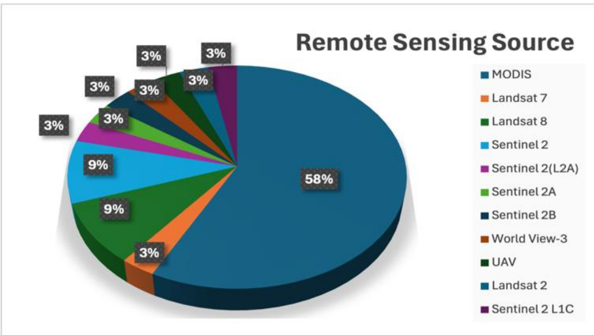

Figure 6. Type of satellites used in the study

4.1.5. RQ5: what are the most used features?

Meteorological data is crucial for making accurate predictions. The type of meteorological feature depends on the crop being studied. However, there are a certain group of most commonly used features we have encountered in our selected papers such as temperature. This was the most used feature among all the selected studies such as [14], [19], [41], [47], [52], [59], [65]-[75] followed by precipitation in the studies [15], [17], [18], [21], [33], [52], [54], [59], [72], [74]-[76], rainfall [12], [14], [48], [67], [69], [70], [77]-[79], vapour pressure [19], [80] and other meteorological data such as humidity, wind speed, humidity. Soil characteristics such as Nitrogen, Phosphorus and potassium were most used soil features [22], [33], [41], [65], [68], [69], [81]-[83] followed by Soil Ph [22], [41], [50], [54], [76], [82], [84]. Among the vegetation indices obtained from satellite images normalized difference vegetation index (NDVI) [11], [13], [14], [19], [23], [26], [29], [57], [58], [65], [68], [85]-[87] was the most used vegetation index followed by Enhanced Vegetation Index (EVI) [13]-[15], [18], [57], [58], [60], [78], [88], and LAI [23], [29], [56], [62], [75]. Figure 7 shows the total count of the most used features used in the selected papers.

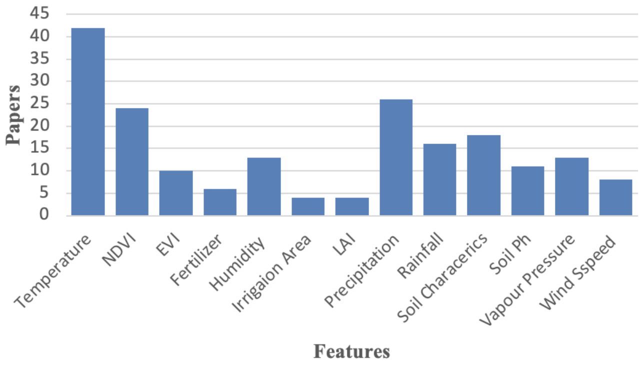

Figure 7. Count of features

4.1.6. RQ6: which among ensembled models and traditional machine learning and deep learning perform better?

Ensembled models are a way of integrating more than one classical model to get advantages of both and increase the accuracy of the prediction. The paper [52] demonstrates the effectiveness of ensemble models that combine CNN and DNN in predicting corn yields. The ensemble models outperformed individual ML models, suggesting that the combination of different types of neural networks can improve prediction accuracy. Similarly, the research [27] also advocates for ensemble models in corn yield forecasting. The optimized weighted ensemble and the average ensemble were found to be the most precise models. Another study [87] used ensemble tree methods, specifically boosted regression trees (BRT) and random forests, for early prediction of winter wheat yield. The results suggest that ensemble tree methods can effectively handle complex interactions between variables and improve prediction accuracy. The study [89] focused on predicting sugarcane yield in Brazil using NDVI time series and neural networks ensemble and also suggested that ensemble methods can be effective in different geographical locations and for different crops.

From these studies, it seems that ensemble methods, whether they are based on classical ML algorithms or DL algorithms, show superior performance in crop yield prediction. The ensemble methods can effectively combine the strengths of multiple models to improve prediction accuracy and precision. However, it’s important to note that the choice between ensemble and classical ML or DL algorithms may depend on the specific problem and data at hand. While ensemble methods have shown promising results in these studies, classical ML or DL algorithms might perform better in other scenarios.

4.1.7. RQ7: what are the limitations and future directions?

With advancing technology of satellites, it has become easier to monitor crops and obtain data for making predictions. However, a large model that heavily relies on satellite data is still very difficult to run because of the very high-resolution satellite images that are typically a couple of gigabytes, and they have to be collected for a certain period to make a historic dataset for predictions making it costly to run. This has however been made a little easier by Google Earth Engine which uses cloud computing for running such heavy computations. But with large study areas, this is still a problem as platforms like Earth Engine have their limitations such as time out limit, and limited size of particular satellite Images for computation at a time. For very large study areas, it’s necessary to buy high cloud storage on platforms like Earth Engine for making calculations or work on very high-end machines which are typically only in Labs. For researchers looking to use these Satellite images directly, they have to be downloaded to perform operations using various frameworks such as Geospatial Libraries and OpenCV. Historic images of an area for a couple of years can easily go over a few hundred gigabytes and more. This requires very high storage capacity and very advanced and capable GPUs for image feature extractions. The cost reduction can be looked as a joint effort of researchers in the field that can set up labs dedicated to crop predictions and other related work to crops, to grow the community and help researchers collaborate which would in turn reduce the cost.

In developed countries like The United States and Canada the Agriculture sector is very organised that the government is able to release a high-resolution crop data layer. The crop can be identified through CDL without any other preprocessing. This is very useful as it allows researchers to eliminate the unnecessary fields or roads and buildings being considered in the dataset. However, there are only a few countries that have been able to do this. In developing countries crop data layers are still unattainable because of mixed agricultural practices and lack of monitoring by the government which makes it difficult for researchers to track down the exact area of the cropland that is to be studied. This makes crop data layers a very crucial part of studies related to crops as they are responsible for the precision of the study as satellite images being used directly cannot provide as a satellite image contains information of not only the cropland but also of surrounding uncropped area that is not needed for study. While it is difficult to make crop data layers in developing countries, efforts can be made by starting to work with small areas that cover a particular state, district or county and further be expanded to other areas of the country. This, however, would require a lot of groundwork as well to organise the agricultural practices so tracking crop fields can be made easier for a particular crop. Multi-source data can also be experimented including different soil features, water, and climate for each crop so the researcher can make informed decisions as to what exact features impact the crop that is being studied. The more relevant VIs such as perpendicular vegetation index (PVI), soil-adjusted vegetation index (SAVI), atmospherically resistant vegetation index (ARVI), solar-induced fluorescence (SIF), and difference vegetation index (DVI) can also be used to further for making accurate studies.

Comparing this study with similar reviews, according to a review [7], the most frequently used features include temperature, soil type, and rainfall, with neural networks and linear regression being the most common algorithms, followed by random forest and SVM. Common evaluation metrics were RMSE and RR^2. Another study [6] noted LSTM and CNN-based approaches as prevalent DL techniques, primarily using the MODIS satellite, followed by Landsat 8 and Landsat 7, with VIs, meteorological data, and yield information as key features. Additionally, [8] identified VIs and satellite data, alongside historical yield and climate data, as frequently used inputs, with random forest and ANN as top algorithms, followed by CNN, using RMSE, Accuracy, and R2R^2R2 for evaluation. Similarly, [9] observed images, precipitation, and actual yield as major features, with CNN, LSTM, ANN, and DNN as common algorithms, using RMSE as the primary evaluation metric. Another review [10] showed CNN and RNN as the most-used algorithms. In comparison, our study highlights temperature and precipitation as primary features, MODIS and Landsat 8 as primary satellites, with RMSE and R^2 as main evaluation metrics, and random forest and SVM as prevalent models, with CNN and LSTM as state-of-the-art techniques. Table 3 represents the comparison among randomly selected papers.

Table 3. Comparison with similar work

Ref	Paper focus	Findings
[46]	Improving crop yield prediction in Morocco.	ML models outperformed statistical models inmaking predictions. ML models achieved R^2 ranging from 0.76 to 0.84.
[52]	County level corn yield prediction using CNN-DNN in US corn belt.	The model made 2019 prediction with RMSE of 866 kg/ha.
[76]	Improving crop yield prediction in China.	Proposed a model that predicts pre season and in season prediction for 5 crops.
[63]	Silage maize yield prediction using time series dataset from NDVI.	BRT had highest R value of 0.87.
[28]	Proposed a framework for wheat yield prediction.	LASSO received highest performance with R^2 of 0.93.

The findings of the research questions in this study highlight that, leading crop yield prediction models include ensemble techniques like random forest and XGBoost, alongside DL approaches such as LSTM and CNN. Each model type offers distinct strengths depending on dataset size and complexity. Ensemble and neural network models work especially well with larger datasets due to their ability to capture complex patterns, while traditional ML models can perform effectively with smaller datasets. Metrics like RMSE, R^2, and MAE are commonly used to evaluate model accuracy and reliability. Data sources span meteorological information from organisations like NOAA, where temperature is a frequently used feature, to satellite-based remote sensing data with vegetation indices like NDVI and EVI, which are essential for monitoring crop health. However, challenges persist, such as the high computational cost of processing satellite imagery and limited crop data availability in developing regions. Future research should focus on improving model efficiency, creating crop-specific data resources in rural areas, and fostering collaborations to support global crop prediction efforts. This summary provides researchers with insights into the latest methods and practices, helping them identify best practices for enhancing prediction accuracy and building on existing advancements.

5. CONCLUSION

This study concludes that data sources are often specific to the area being studied, with meteorological data frequently obtained from organizations like NOAA and soil data from Food and Agriculture Organization (FAO). Satellites such as MODIS are widely used for calculating vegetation indices like NDVI and EVI, while newer, high-resolution satellites like Landsat-8 provide improved precision. Efforts to develop crop data layers in various countries could make satellite data more accurate, especially in rural areas. Combining these vegetation indices with meteorological data, such as temperature, rainfall, humidity, and soil characteristics, creates robust datasets for crop yield prediction. Tree-based models like random forest excel with smaller datasets due to their ability to combine weak and strong learners, while SVM are effective in high-dimensional spaces and for modelling non-linear boundaries. For larger datasets, DL models like ANN and CNN-LSTM outperform traditional ML models by capturing complex patterns in data. However, challenges remain, including the high cost of processing high-resolution satellite imagery and limited access to crop data in developing regions. Future advancements in satellite and cloud computing technology could help overcome these challenges, while collaborative labs and localized studies may improve data accessibility. Expanding datasets to include advanced vegetation indices and multi-source data could further enhance prediction accuracy and support the development of scalable, generalized models for diverse crops and regions.

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