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Machine Learning Techniques for Cereal Crops Yield Prediction: A Comprehensive Review

Souand P. G. Tahi[1*], Vinasetan Ratheil Houndji[1,2], Kolawolé Valère Salako[1], Castro G. Hounmenou[1] and Romain Glele Kakaï[1]

[1]Laboratoire de Biomathématiques et d'Estimations Forestières, Faculty of Agronomic Sciences, University of Abomey-Calavi, 04 BP 1525 Cotonou, Benin
[2]Institut de Formation et de Recherche en Informatique, University of Abomey-Calavi, 01 BP 526 Cotonou, Benin

*Corresponding author: souandtahi@gmail.com

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Abstract: Cereals are sensitive to small changes in complex combinations of biotic and abiotic factors. Such a complexity can be deciphered using techniques such as Machine learning (ML). Using the PRISMA approach, this paper explores the features and ML techniques in cereal yield prediction based on 115 articles from 2007 to 2023 in six databases. Results showed that most data in the articles were from secondary sources and only 28.68% used experiments or primary data. China (31) and the United States (18) contributed most. Wheat (48%), maize (33%), and rice (17%) represented the most studied cereals. Climate, remote sensing data, and soil parameters were the most used predictors. The most frequently used ML techniques for cereal prediction were support vector machine (SVM) (51%), multi-layer perceptron (MLP) (41%), linear regression (34%), random forest (RF) (24%), and XGBoost (20%). However, RF, MLP, and SVM models were the best-performing techniques to predict grain yield based on reported R-square and mean absolute error (MAE). The models in the studied articles generally performed well from test data, with an R-square between 0.7 and 1. The study further reveals that the data's availability and quality are the main obstacles to using ML models for crop prediction.

Keywords: Cereal; Deep learning; Machine learning; PRISMA; Yield prediction.

1. INTRODUCTION

Cereals are plants whose grains feed humans and domestic animals [1], and are also used in bioenergy production [2, 3]. They are the most widespread group of crops worldwide. Rice, wheat, maize, sorghum, and millet are stapled grains that billions worldwide depend on for everyday existence [4]. Moreover, rice, wheat, and maize are stapled foods in America, Asia, and Africa. However, the demand for rice in Africa is exploding [5]. Cereal is at the heart of food and nutritional security [6] and is grown to feed humans and animals by providing 60-75% of caloric intake and 8-13% of protein [7]. Moreover, it plays an essential role in the world economy [8]. According to [9], in 2027, cereal consumption will increase due to the rise in food and feed consumption in developing countries. Despite its importance in the world diet, its yield in developing countries remains low. Many factors affect crop yields, including landscape, soil quality, pest infestations, genotype, water quality, accessibility, climate conditions, and harvest planning [10], [11], making prediction a difficult statistical task. However, it is essential to estimate crop yields accurately based on production factors that determine the yield. Nowadays, crop prediction is receiving increasing attention from researchers around the world [11], particularly due to the growing rate of malnutrition in the world and global climate change.

Crop yield prediction follows a non-linear process, making standard models less suitable in recent years [12]. Machine learning (ML), an advanced statistical technique, is well-adapted for yield prediction [13]. ML is an artificial intelligence (AI) technique that teaches computers to learn from experience. It predicts crop yields more accurately than classical statistical techniques (e.g., least squares and maximum likelihood) [14]. ML has been widely used for crop yield modelling and prediction. Some reviews have been carried out to synthesize trends and discuss the way forward. For example, [15] provided a review of the use of ML algorithms to predict crop yield, focusing on palm oil yield prediction. The authors presented the current state of palm oil, described the fundamental aspects of crop yield prediction, and conducted a review of ML-based crop yield prediction algorithms. Algorithms are composed of instructions and operations performed on data precisely to produce a result and solve complex problems. Patrício *et al*. [8] conducted a systematic review to identify the applicability of computer vision in precision agriculture to produce the five most-produced grains in the world: maize, rice, wheat, soybean, and barley. They found that computer vision and AI have the potential to improve crop management practices in precision agriculture. Klompenburg *et al*. [11] also performed a systematic literature review to extract and synthesize the algorithms and predictors

used in crop yield prediction studies. Following their analysis, the authors found that temperature, rainfall, and soil type are the most used features and artificial neural networks are the most used algorithms for yield prediction. Bali *et al*. [16] explored and evaluated different ML and deep learning techniques used in crop yield forecasting and the performance of hybrid models trained by combining more than one technique. The findings showed an excellent inclination to hybrid models and deep learning techniques for crop yield prediction. The study also revealed that temperature and rainfall significantly influence the yields of different crops. Chlingaryan *et al*. [14] discussed ML techniques used for accurate crop yield prediction and nitrogen status estimation based on research developed over the past 15 years. They concluded that rapid advances in sensing technologies and ML techniques would provide cost-effective and comprehensive solutions for improved crop and environmental status estimation and decision-making.

The existing reviews on ML techniques to predict crop yields mostly focused on several crops and summarised trends for crops together, overlooking crop-specific patterns. As such, the results obtained are not necessarily applicable to specific crop groups. This limits the relevance and applicability of the results, specifically to cereals. Cereals are characterised by intrinsic features that make them very sensitive to genetic variability, fluctuations in biotic (e.g., pests), and abiotic (e.g., nutrients, climate) factors. These characteristics raise the crucial question of whether ML methods that predict crop yields are effective in deciphering such complexity when making cereal predictions. Variations in water requirements, temperature thresholds, and soil conditions, combined with the complexity of environmental factors, can influence the performance of ML methods on cereal yield prediction. This study highlights potential research gaps in a particular area and guides practitioners and researchers looking to conduct new research on cereal prediction. The study presents a synthesis of ML techniques and features used for cereal yield prediction. It explicitly identifies the different and most relevant ML approaches for cereal yield prediction. In particular, we have identified: (1) the main cereal crop species used in studies of yield prediction, (2) the predicting factors, (3) the nature and scale of the data used, (4) the most important models used, (5) the model hyper-parameters, (6) the comparison metrics used for cereal yield prediction (7) the accuracy of the best models obtained, (8) the geographical distribution of countries that contributed to the literature on cereal, (9) the links between data size and models precision, (10) the relationships between data size and geographical distribution of countries, the link between data size and data scale as well as the link between data size and models precision, and (11) the relationships between best models and their precision.

2. METHODOLOGY

Systematic reviews are a research methodology approach that focuses on a specific research question and is distinguished by its rigor, structure, and reproducibility, making it less susceptible to selection bias. The systematic review carried out in this study selected the scientific articles following the PRISMA guidance (Preferred Reporting Items for Systematic Reviews and Meta-Analysis). See Figure (1) [17]. This technique was selected because it is a well-defined methodology tailored to systematic reviews. It requires the prior definition of inclusion and exclusion criteria to be used for article selection before the study begins, and these criteria cannot be modified during the selection process. Thus, it enables an organised and systematic analysis of relevant articles from multiple databases to ensure the literature review is transparent, comprehensive, and reproducible. During the identification phase, different search engines were used: Google Scholar, Science Direct, Institute of Electrical and Electronic Engineers (IEEE), Multidisciplinary Digital Publishing Institute (MDPI), Scopus, and Web of Science. To access the various scientific articles, we connected different keywords by Boolean operators: ("machine learning" OR "deep learning" OR "ensemble learning" OR "support vectors machine" OR "random forest" OR "XGBoost" OR "decision tree" OR "K-nearest neighbors" "OR "Artificial neural networks" OR "Recurrent neural network", OR "Long short-term memory", OR "Multilayer perceptron") AND ("cereals" OR "grains" OR "oats" OR "wheat" OR "fonio" OR "maize" OR "millet" OR "barley" OR "paddy rice" OR "rye" OR "sorghum" OR "triticale" OR "teff" OR "quinoa" OR "buckwheat" OR "spelt") AND ("yield prediction" OR "yield forecasting" OR "Yield estimation"). A total of 360 papers were collected. The main criteria of selected papers were based on the relevance of the study and the originality of the work. A first selection was made, during which 51 duplicate papers were excluded. After the screening, we made a second selection according to the title of the papers (52 papers). During this second step, book chapters (12), thesis works (5), and literature reviews (8) were excluded. A third selection followed after reading the abstracts and keywords. Only papers not related to the subject (117) were excluded. In total, one hundred and fifteen (115) scientific documents with a detailed explanation of the methodology and the strength of the reported results were studied. Several data were collected from the selected papers. Firstly, the studied crops and the ML models used to predict its yield were collected. Moreover, the input variables and hyperparameters associated with the ML adjusted to optimize the models' performance were gathered, followed by the comparison metrics used to evaluate model performance. In addition, the accuracy of important models was gathered, as well as the sample size, the training data percentage, and the data scale. The data partitioning techniques used in each study and the country of origin of the data were also reported from each paper. Finally, the strengths, weaknesses, and perspectives were identified.

Once the data was collected, analyses were carried out to summarise the trend. Descriptive statistics were used to explore and summarise trends for each variable. Bar plots were used to visualise the frequency distribution of categorical variables (e.g., crops and ML techniques). In addition, trend curves were used to highlight the evolution of the ML techniques used in agriculture and the number of publications across time. All descriptive statistics were carried out in R 3.6.3 software with the ggplot2 package to summarise the cereal crops, ML methods, input variables, hyperparameters, comparison metrics, models precision, percentage of training data, data size, data scale, data partitioning techniques, the relationship between data size and precision, the link between data scale and model used, the link between data size and geographic location, and the relation between best models and precision. The geographic location of the data collection sites was mapped using ArcGIS 10.8 software.

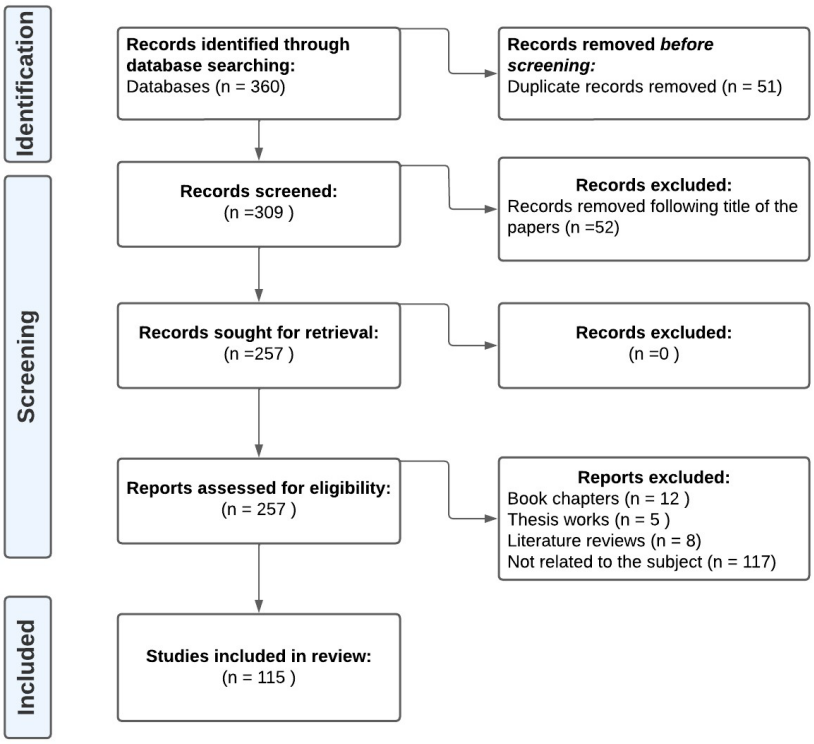


Figure 1. Flowchart summarising the methodology.

3. RESULTS AND DISCUSSION

3.1. Trend of Publications on the Use of ML Techniques in Cereal Yield Prediction

The number of publications by year (Figure 2) shows that the use of ML methods in cereal yield prediction has increased during the last four years. About 36% (41 papers out of the 115) of the selected papers were published in 2021. This percentage shows the importance of ML methods in agriculture in recent years. It demonstrates the value placed on cereal yield forecasting, given its critical importance to food security and agricultural sustainability.

The geographical distribution of countries contributing to ML applications in cereal prediction is summarised in Figure 3. For this purpose, only the data sources used in each paper were considered. If the data of a scientific paper have several provenances, all of them were considered. Research on cereal yield prediction using ML methods is spread worldwide. Thirty-three (33) countries contributed to this study. However, the contribution is more significant in China and the United States (31 and 18 scientific papers, respectively out of the 115 papers). There is a relatively considerable contribution from the Asian continent. Outside China, India (11), Australia (6), and Pakistan (4) also contributed to the yield prediction. However, contributions are relatively low in Africa, with only one publication per country for ten countries. Australia and New Zealand are interested in ML for yield prediction.

3.2. Most Studied Cereal Crops

The literature survey of ML methods used for yield prediction identified six cereal species (Figure 4) which are: maize (*Zea mays*), rice (*Oryza sativa*), wheat (*Triticum aestivum]*), barley (*Hordeum vulgare*), sorghum (*Sorghum bicolor*), and jowar (*Sorghum bicolor*). Wheat (48.7%, 56 out 115), maize (33.9%, 39 out 115), and rice (17.4%, 20 out 115) were of particular importance. The interest in these three crops may be related to the fact that they are the three most widely grown and consumed cereals worldwide. In addition, winter wheat is one of the world's major crops [18]. Its production is more significant than others. According to [19], rice, maize, and sorghum are the most grown cereals in Africa. Moreover, rice and maize represent China's principal crops and play a crucial role in food security in southwest China. According to the report, rice is the second most-produced grain in yield and is a staple food globally. China supplies 21% of the maize produced worldwide [20]. As reported by [9], the volume of cultivated maize increased in 2017, exceeding that observed in 2016.

3.3. Models Used for Yield Prediction and Best Prediction Models

3.3.1 Concept Clarification

Several ML models were used and compared to predict cereal yield. In this study, we grouped these techniques into four categories based on the nature of their approach, complexity, and ability to model specific data types: ensemble learning, classical, neural networks, and rare. Classical ML methods are traditional techniques widely used before deep learning. They use established mathematical principles and statistical concepts to make predictions and decisions. These methods offer a more classical approach to learning. They are adapted to different types of data and problems and include decision tree (DT), support vector machine (SVM), linear regression (LR), k-nearest Neighbor (KNN), ridge regression (RR), least absolute shrinkage and selection operator lasso.

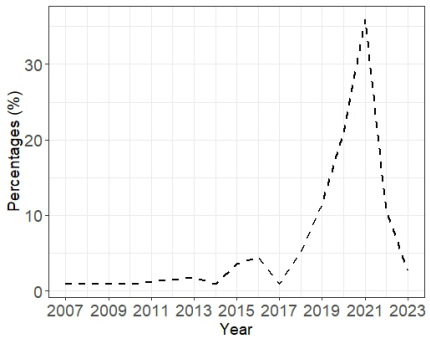


Figure 2. Number of publications per year.

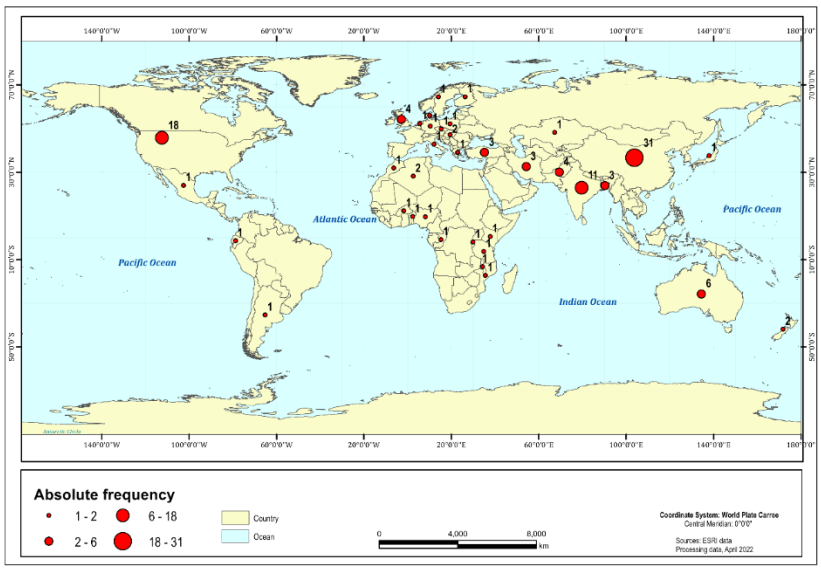


Figure 3. Geographical distribution of data.

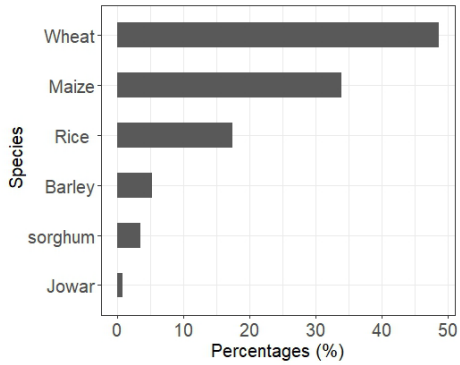


Figure 4. The investigated cereal crops using ML models for yield prediction.

Ensemble learning methods combine several classical techniques, build on their strengths, and mitigate their weaknesses, producing more robust, higher-performance models. This category improves the accuracy of predictive models, particularly tree-based models (random forest (RF), extreme gradient boosting (XGBoost), extremely randomized tree (ERT), stacked regression, light gradient boosting machine (Light GBM), gradient boosting, bagging tree, Adaptive Boosting (AdaBoost), and cubist (CUB)) [21, 22].

Neural networks are inspired by the human brain's ability to solve complex problems. They consist of hidden layers and fundamental processing units available in various architectures. The most used include multi-layer perceptron (MLP), which have several hidden layers, convolutional neural networks (CNNs), mainly for computer vision, which include convolution and subsampling layers, and recurrent neural networks (RNNs), which are designed to process sequential data. Supervised Kohonen networks (SNKs) are also part of this category of methods [23]. The works that used neural networks (NN) with less complex architectures were replaced by MLP. The models with unique characteristics were grouped into the Rare (gaussian process regression (GPR), gaussian linear models (GLM), and other models). The other sub-category referred to less frequently used models (linear and quadratic discriminant analysis (LDA and QDA), polynomial regression, gaussian naïve Bayes (NB), geographically and temporally weighted regression (GTWR), geographically and temporally weighted neural network (GTWNN), autoregressive integrated moving average (ARIMA), multivariate adaptive regression spline (MARS), gene-expression programming (GEP), *a priori*, polynomial regression (PR), optimized weighted ensemble (OWE)).

3.3.2 Prevalent and Optimal Models: A Projection of the Best-Performing Approaches

Classical methods were widely used for cereals yield prediction, followed by ensemble methods. Neural network methods were less commonly used to predict cereal yield. SVM models represented the usual method for yield prediction, while MLP was the second usual method in the works studied, followed by LR, the third ML used for cereal yield prediction. At the same time, XGBoost and RF were much more commonly used in the ensemble learning category and were, respectively, the fourth and fifth most widely used for grain yield prediction (Figure 5(a)). These results contradict those obtained in the review by [11], which identified ANN and LR as the usual methods for predicting crop yield. This contradiction may be linked to the complexity of the data, their scale, or their size. Moreover, most existing studies identified RF as the most widely used method for crop forecasting. In contrast, the present study reveals it as the fifth most used method and the best model for cereal yield prediction. The intensive use of SVM is due to its flexibility in representing complex functions and its resilience to overfitting. Most original papers used LR models as a baseline to evaluate the performance of ML methods. The results obtained with MLP are corroborated by [11], who observed that neural networks were widely used to predict crop yields. SVM was also mentioned among the most used techniques in their work. However, its use is not significant. Table 1 presents the functioning, strengths, and weaknesses of these five usual MLs for predicting performance.

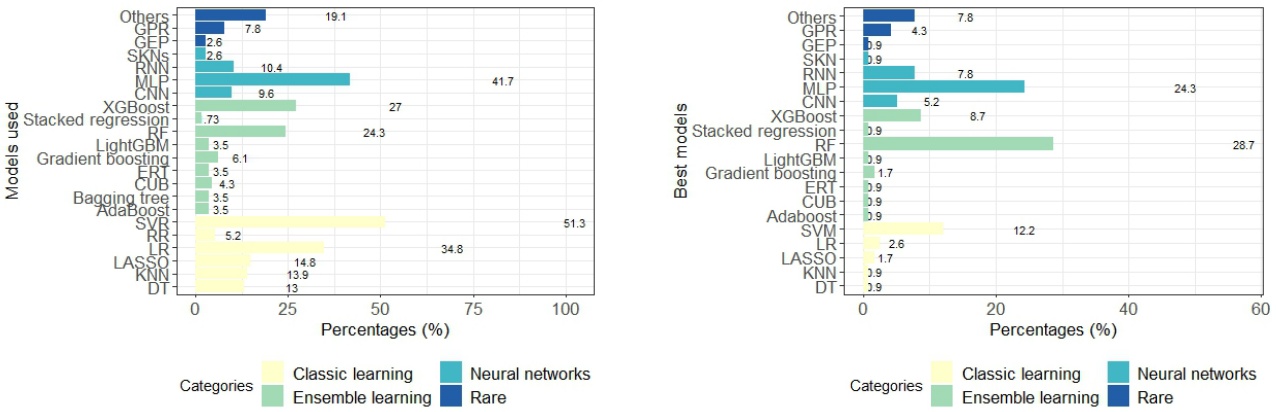


Figure 5. Usual and best ML models and trend of tree best models. (a) Models used for prediction, (b) Best models for cereal prediction, (c) Best models following year.

The best models obtained in the investigated papers using the percentage were presented in Figure 5(b). Ensemble methods (RF and XGBoost) provided good crop yield prediction, followed by neural network models (MLP). As for classical forms, they offered little in the way of good grain yield prediction. However, the accuracy of SVMs is better predicted grain yield in this category. RF is an ensemble learning technique that combines some decision tree models. This trained combination results in a more accurate and stable prediction. RF prevents an over-trained individual tree from affecting how the model generalizes to new data. Wheat yield using was modelled using prior information, satellite, and climate data in Mexico [24]. Based on 5823 observations, they obtained a better prediction with the RF model, whose performance was compared to partial least squares regression (PLS), ridge regression (RR), LASSO, KNN, XGBoost, and SVM models. Similarly, [25] predicted early winter cereal yield from LR, LASSO, RF, DT, KNN, and bagging regression methods. They note good yield accuracy with random forests. Similar results were observed in various other works [26, 27, 28, 29]. The excellent accuracy of other ensemble techniques results from their ability to reduce noise, variance, and bias [30, 31, 32]. [33] and [34] observed excellent prediction of maize with the XGBoost model. In addition, [35] had a good prediction of wheat with XGBoost. To understand the trend of models over time, we plot the trend of the three best models by year (Figure 5(c)). We observed an increase in the use of the SVM, RF, and MLP models from 2014 to 2021. This growth may be related to the models' abilities to process complex and varied data and their adaptability to the specificity of the cereal data to be supplied. However, the number of works using MLP in 2021 increased compared to previous years. Although the RF models were still the most used, the use of neural network models in cereal yield prediction was increasing over time and will soon become the reference method for cereal yield prediction. The effective use of neural networks is supported by the fact that, unlike conventional statistical approaches, they offer great capacity for generalization and consider the non-linearity, noise of data, multi-collinearity between input variables, and the dynamic nature of data [36].

Figure 6 presents the link between the models and their performance. Most efficient models predict cereal yield with an R-square between 0.70 and 0.90. However, the XGBoost, SVM, RF, ERT, MLP, and some models in the rare category predicted cereal yield with an R-square between 0.90 and 1 (Figure 6(a)). The SVM, RF, and MLP models gave an MAE less than or equal to 0.10 ton/ha. Most models obtained MAE between 0.50 and 1 ton/ha. However, RF and SVM sometimes have MAE greater than 1 ton/ha (Figure 6(b)). In addition, MLP, RF, LR, gradient boosting, and rare models predicted cereal yield with RMSE less than 0.10ton/ha (Figure 6(c)). Hence, SVM, gradient boosting, MLP, and RF models give higher accuracy for cereal yield prediction.

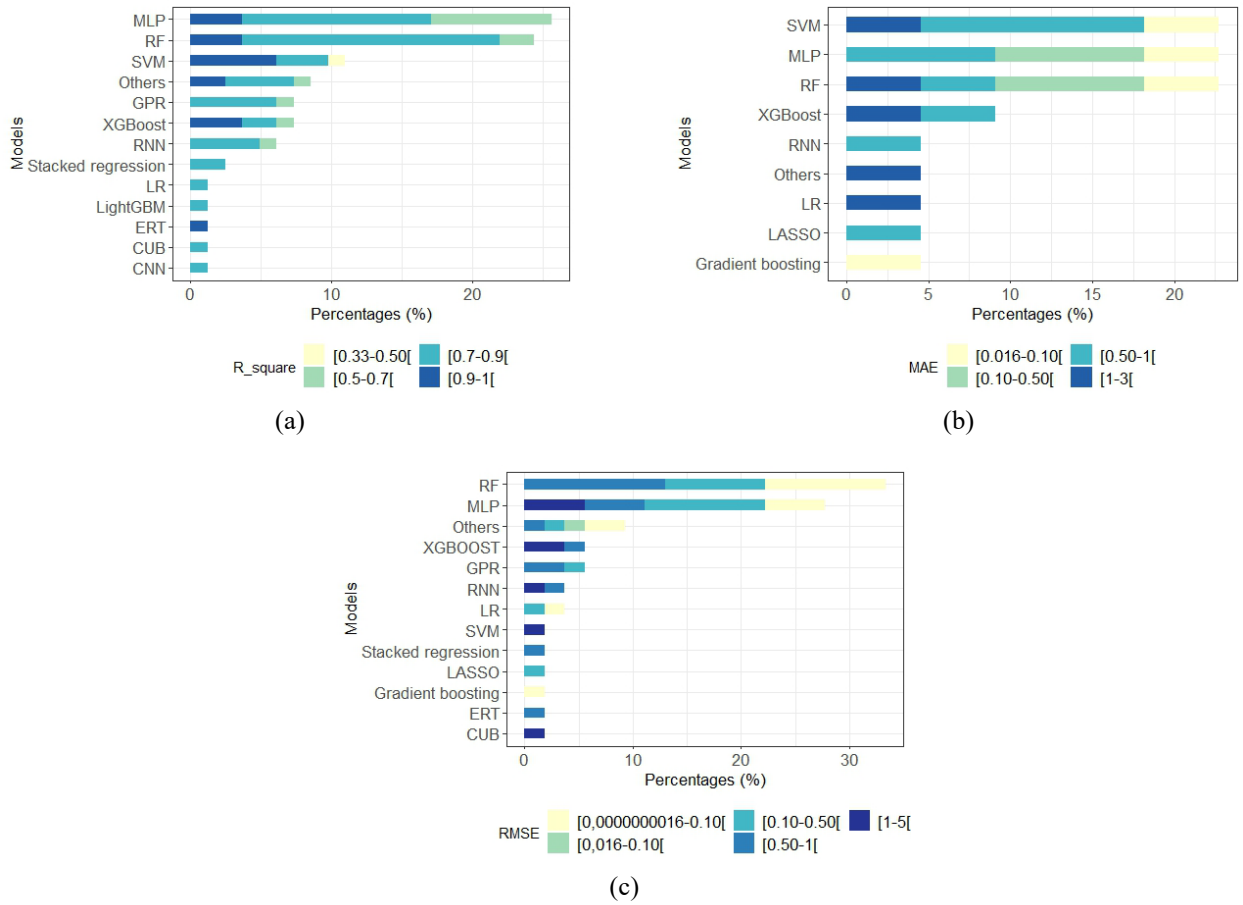


Figure 6. Relationship between the models and their performance. (a) Models and adjusting coefficient, (b) Models and mean absolute error, (c) Models and root mean squared error.

Table 1. Functioning, strengths, weaknesses, and commonly used hyperparameters of the five standard ML methods for predicting cereal yield.

Models	**Functioning**	**Strengths**	**Weaknesses**	**Usual hyperparameters**
RF	It constructs multiple separate decision trees. The algorithm integrates the forecasts from each tree for the ultimate prediction. Two crucial random selections are made during this process: one based on variables (feature sampling) and the other on observations (tree bagging).	Random Forests are less prone to overfitting and are less sensitive to noise. It is used for both classification and regression problems	Need a large number of trees for the algorithm's effectiveness. The algorithm is slow for real-time predictions when many trees are used.	Maximum depth, maximum nodes minimum split, minimum leaf, number estimators, maximum samples, maximum features
XGBoost	The process iteratively integrates the predictions of several separate models, most commonly decision trees, to create a predictive model. For the algorithm to function, weak learners are gradually added to the ensemble, with each new learner concentrating on fixing the mistakes caused by the previous ones. A gradient descent optimization method minimizes a preset loss function during training.	It handles large datasets easily. It is flexible and offers several model customization features, including regularization and cross-validation.	XGBoost is a complex algorithm that can be challenging to interpret. Because of all of its hyperparameters, it requires extra training time. It can be memory intensive and is not suitable for low-capacity systems.	Maximum tree depth, Minimum child weight, Learning rate, Number of boost rounds

MLP	MLP has one or more hidden layers with several neurons stacked on each other, as well as input and output layers. It processes input data through interconnected layers of neurons, applying activation functions to introduce nonlinearity and adjusting weights through forward propagation and backpropagation to make accurate predictions for various tasks.	It resolves intricate nonlinear issues and functions well with big and tiny input data.	MLP provides high computational effort due to its iterative nature. In addition, its performance is highly dependent on the local feature communication mechanism, which can limit its effectiveness.	Number of hidden layers, the number of units for each hidden layer, the learning rate, the activation function, and algorithm learning
LR	The link between the explanatory and explosive variables is best described by a linear equation found using linear regression (LR). To do this, the least-squares method is used to fit a line to the data. The line attempts to reduce the residuals' sum of squares. The difference between the explanatory variable's real value and the line is known as the residual. Iterative search is used to find the best-fit line.	It is straightforward to interpret. It is susceptible to over-fitting, but this can be avoided by using dimensionality reduction techniques,	It is vulnerable to outliers	
SVM	The SVM algorithm finds a hyperplane in the data space that generates the most considerable minimum distance (margin) between the samples that belong to various classes using a training set of samples divided into classes.	It is more productive in high-dimensional spaces, and can handle small datasets, and is robust to noise.	It is not adaptable to extensive data or when target classes overlap. Moreover, the kernel choice can significantly affect an SVM's performance.	Kernel, precision, regulation parameter.

3.4. Models' Performance

3.4.1 Popular Predictors Used in Cereal Yield Prediction

Many predictors affect cereal yield and require monitoring. Approximately 75 predictors were identified and categorised into eight groups: climate factors, vegetation index data, soil properties, irrigation information, growing days, fertilizer, areas, and other categories. Table 2 lists the categories of predictors considered and their relative importance. Most papers (65.2%, 75 out 115) investigated climatic conditions regarding cereal yield prediction. Temperature (89.33%, 67 out 75) and precipitation (98.66%, 73 out 75) comprised most of these climate parameters. In addition, 43.5% (50 papers out of the 115) of the publications considered used vegetation index data. The most interesting factors in this category were the normalized difference vegetation index (NDVI) (72%, 36 out 50) and enhanced vegetation index (EVI) (28%, 14 out 50).

Furthermore, 26.1% (30 papers out of the 115) of the scientific articles examined make use of different soil characteristics. These characteristics included soil testability, pH, clay, sand, organic matter concentration, soil electrical conductivity, and soil organic carbon. The observed results are corroborated by [11], who concluded from their literature review that temperature, precipitation, and soil type were the factors studied to predict yield. Similarly, [37] identified remote sensing, climatic parameters, and edaphic parameters as the main predictors that impact crop yield. These results show the impact of these factors on grain productivity. Integrating and analyzing them together can provide valuable information to support agricultural decision-making and help improve agricultural productivity. Agricultural yields are increasingly dependent on climate parameters [13]. These parameters threaten the progress made in the world's fight against hunger and malnutrition. Remote sensing technologies are early diagnostic tools that can counter potential production problems and their negative impact on crop productivity. [38] integrated the maximum enhanced vegetation index (EVI) with ML regression (MLR) models to estimate wheat. They concluded that early prediction of crop yield and its spatial distribution in the region enables the formulation of effective agricultural policies for sustainable social, environmental, and economic progress. Using vegetative indices taken from multispectral images, [39] found that the performance of the RF model is improved when the NDVI, normalized red edge difference (NDRE), and normalized green vegetation index difference (GNDVI) are combined. Only a few studies have examined fertilizer, water requirements, grain characteristics, geographical scale, and many other yield predictors. Future work must develop models for predicting cereal yields based on under-researched factors.

Table 2. Predictors for cereal yield prediction.

Input variables	Percentages (%)	Input variables	Percentages (%)
Weather	65.2	Growing day	5.2
Soil properties	26.1	Fertilizer	7.8
Vegetation index	43.5	crops fraction	2.6
Others	12.1	Area	3.5
Irrigation information	6.2		

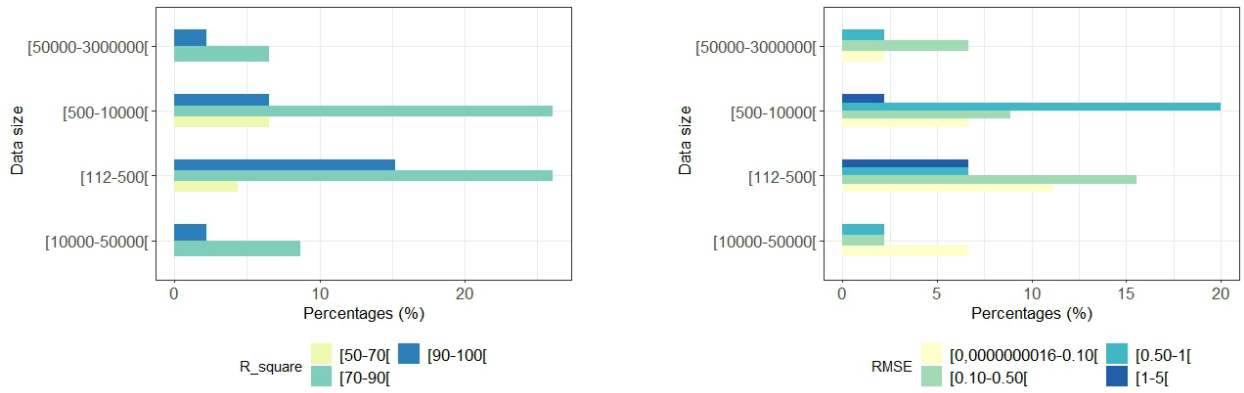
3.4.2 Data Size, Partition and Scale

Seventy percent (70%, 80 out 115) of the analyzed publications used data from a secondary source. Most of them had a regional, national, or continental scope. Only 28.7% (24 papers out of 115) utilised local scale (primary) data. A few authors made use of synthetic data. However, 43.5% (50 papers out of 115) of the publications did not specify the data size used. Most gave information on the number of years of collection without providing any other details. For those who reported it, the data size ranged from 112 to 3,100,000. A total of 44.6% (29 papers out of 65) used data sizes less than 500, while 35.4% (23 papers out of 65) used a data size between 500 and 10,000. Very few studies have utilised large datasets to predict crop yields. Nevertheless, using large data in ML is significant as it mitigates overfitting and enhances the model's accuracy.

To model data, all reviewed papers partitioned the data into two parts: training and testing. 44.4% (51 out of 115) of papers specified the percentage of data used for training models. In this set, 45.1% (23 out of the 51) and 37.3% (19 out of 51), respectively, used 70–80% and 80–90% of the dataset. Training data is the backbone of ML projects. It allows the ML method to perform the given task and improve the prediction. Some authors resampled their data using *K* cross-validation. Therefore, 38.3% (44 papers out of 115) of the publications under investigation employed *K* cross-validation. For improving model performance and making decisions based on the results of predictions, *K* cross-validation is essential. Different *K* values were used, though $K = 10$, employed in 59.1% (23 out of 51 papers) of these studies, were the most notable. However, applying cross-validation on a small dataset can sometimes lead to overfitting.

The relationship between data size and countries revealed that only China and the USA (3.07%, 2 out 65) used a high data size, between 500,000 and 3,000,000. In addition, Kazakhstan republished (1.5%, 1 out 65), China (6.15%, 4 out 65), and the USA (3.07%, 2 out 65) are the only ones to have used data sizes between 10,000 and 50,000 for cereal prediction. The other countries have used small data sizes. The United States, China and Kazakhstan have used large databases to forecast agriculture yields, thank to significant efforts in collecting and organising this data. Most papers of these countries have used satellite data for prediction. The development of ML techniques depends on the presence of quality databases and features used. The data size used in African countries to predict cereal yields was relatively low because of the non-existence of databases.

From the relationship established between data size and model accuracy, there was no direct relationship between size and coefficient of determination. However, some papers that trained models with data sizes lower than 10000 sometimes provided an R-square between 0.5% and 0.7% and RMSE higher than 1 ton/ha (Figure 7). Thus, the larger the data size, the more accurate the model. For the machine to learn from the data effectively and produce accurate results, a minimum amount of data ($n = 10000$) is required. Large data size is only sometimes the determining factor for good accuracy. It allows the model to learn from more complex and generalizable data and avoid overfitting. The selection of input variables also plays a role in the accuracy of the models. The selection of the variables eliminates the less useful variables and lowers the chances of overfitting. Thus, it allows the model to focus on the most predictive characteristics, leading to more accurate and reliable outcome predictions. Figure 8 illustrates the relationship between the models used to predict grain yield and the scale of the data. RF models were widely used to predict yield, regardless of the data. For regional data RF (23.48%, 27 out 115) and MLP (21.74%, 25 out 115) were the most popular models while RF (12.17%, 14 out 115) and other models (13.05%, 15 out 115) were frequently used in local data. The SVM (16.52%, 19 out of 115) and RF (17.39%, 20 out 115) models were used to model national data. Data at the continental scale were most frequently used with models from other groups (2.61%, 3 out 115) and RF (1.72%, 2 out 115). The RF model was efficient and suitable for handling datasets of different scales: local, regional, national, or continental. The full list of references is summarised following the best models (Table 3).



(a) (b)

Figure 7: Link between data size and model precision: (a) Data and R-square, (b) Data and RMSE.

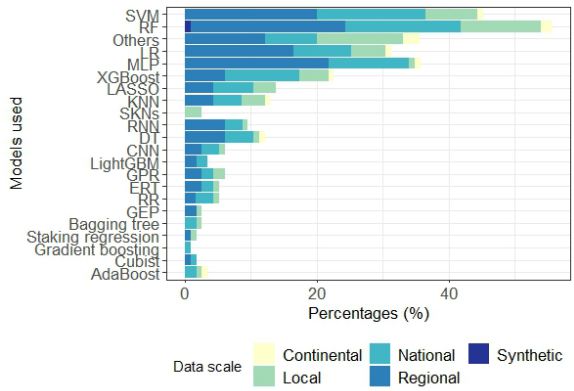


Figure 8. Link between ML models and data scale for yield prediction.

Table 3. Accuracy of ML models.

References	Type of cereal	Best model	References	Type of cereal	Best model
[48], [49], [10], [50], [51], [52], [53], [54], [55], [56], [57], [27], [58], [59]	Rice, wheat, maize	SVR	[119]	Jowa, wheat	ERT
[60], [21], [62],[24], [63],[64], [65], [27], [28], [66],[26], [67], [39], [29], [68], [69],[70], [71], [72], [73], [74], [75],[76],[77], [78], [79], [80], [81] , [139] , [140], [141]	Maize, wheat, rice, sorghum	RF	[130], [31], [131]	Maize	Gradient boosting
[29],[75],[82], [83], [84], [85], [86], [16], [87], [143],	Wheat, rice	RNN	[126], [127], [128]	Rice, wheat, maize	DT
[88], [41], [89], [90], [91], [92],	Barley, wheat	CNN	[27], [136], [37], [137], [138],	Wheat, maize, rice	GPR
[57], [93]	Maize, wheat	Lasso	[129]	Maize	Stacking regression
[79], [94], [32], [95], [30],[96], [34], [35], [33], [96]	Rice, wheat, barley, maize	XGB	[132], [133], [121], [135], [124]	Maize, wheat	Others
[68], [97], [99], [100], [101], [102], [103], [104], [105], [106], [107], [108], [109], [110], [111], [112], [113], [114], [115], [116], [117], [118], [119], [134], [142],	Maize, rice, wheat, barley	MLP	[51]	Wheat, maize	LM
[44]	Wheat	SKN	[125]	Maize	Cub
[120]	Wheat	Adaboost	[123]	Rice	GEP
[122]	Wheat	Light GBM	[25]	Wheat	KNN

3.5 Evaluation of the Model's Precision

3.5.1 Hyperparameters Specification

A hyperparameter is a tuning parameter defined before the learning process and may directly affect the learning quality of a model [40]. When input variables are properly selected, the hyperparameters define the highest level of model complexity and its learning capacity. Good optimisation of the hyperparameters can lead to better accuracy of the model [41]. However, the number of hyperparameters to optimise can vary from one method to another. Two to three hyperparameters for SVM are considered (C, gamma, kernel). We can have twenty hyperparameters for decision trees, while for deep learning methods, the number of hyperparameters to optimize can quickly become very large.

The model hyperparameters can be calibrated more accurately using several techniques. They were the Bayesian search, the random search, and the grid search [42]. Most of the studies used random searches. 56.5% (65 out of 115) of studies mentioned using hyperparameters. The most frequently reported hyperparameters were "number of hidden layers", "Kernel function", and "learning rate". However, not all the values or functions assigned to these hyperparameters are specified. The hidden layer between the input and output layers receives a set of weighted inputs and produces output through an activation function. The values assigned to this for cereal prediction vary between 1 and 26. Among the nineteen works that specified the number of hidden layers used, 78.9% (15 out of 19) used 1 to 5 hidden layers, and 15.8% (3 out of 19) used 5 to 10 hidden

layers. The kernel function transforms the input data into the form required for their processing. Various kernel functions are used for specific transformations: linear kernel for linear separability, polynomial kernel for polynomial relationships, sigmoid kernel for relationships resembling sigmoid functions, and RBF kernel for infinite-dimensional space transformations. The RBF function was frequently used (55.5%, or 15 out of 27), followed by the linear function (25.9%, 7 out of 27). The learning rate was also used as a tuning parameter in the optimization algorithm that determines the step size at each iteration while moving toward a minimum loss function. It was ranged from 0.0001 and 1. Approximately 35% (7 out of 20) used a rate between 0.01 and 0.1 (Table 4).

3.5.2 Evaluation Metrics

Metrics are used to evaluate the performance of a model. They are used according to whether we are in classification or regression. Most of the metrics listed were regression metrics. However, some classification metrics (precision, sensitivity, accuracy, area under the curve…) were used to evaluate cereal yield prediction models [43, 44]. Table 5 shows the commonly used metrics to evaluate cereal yield models. Root means square error (RMSE), coefficient of determination (R-square), and mean absolute error (MAE) were the most common. These were also noted as typical metrics by Thomas van Klompenburg *et al*. [11] for assessing performance prediction algorithms. Indeed, RMSE measures the average difference between the predicted values by the model and the actual values. It is beneficial for assessing the accuracy of predictions. This statistic indicates that a prediction is accurate when its performance approaches zero. However, RMSE can be challenging to interpret based on the magnitude of the error. Additionally, it may be sensitive to outliers and influenced by the scale of the data [45]. The coefficient of determination (R-square) is a metric that measures the proportion of the variance of response values explained by the model. It is a valuable gauge of how well the model fits the data; a number nearer 1 denotes a more accurate model. However, a low R-square doesn't necessarily mean a poor model and a high R-square does not guarantee a good fit for the data. Consequently, it is advised to utilise it in addition to error curves [46].

The MAE explains the average of the absolute differences between predicted and actual values. It measures the average precision of the model. A model is considered better if its value is nearer 0. It is not as susceptible to outliers as RMSE is. Regardless of their significance or influence, every observation has the same weight. Furthermore, it does not offer any details regarding the direction of errors [47]. RMSE, MAE, and R-square worked in tandem and offered several viewpoints on model performance. They were frequently used together to guarantee the accuracy of predictions. The equations can be written as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{I=1}^{n}(\in_i)^2} \tag{1}$$

$$R^2 = \frac{\sum_{i=1}^{n}(\in_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2} \tag{2}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n} | \in_i | \tag{3}$$

where $\in_i$ is the prediction error between each observation *i* and measurement, *n* is the number of observations, $\bar{y}_i$ is the mean of true value and y_i is the actual value.

Table 4. Hyper-parameters used in literature.

Hyper-parameters	Percentages (%)
Kernel function	
Linear	25.9
Logistic	3.7
Polynomial	14.8
RBF	55.5
Hidden layer	
[1-5[	78.9
[5-10[	15.7
[10-26[	5.2
Learning rate	
[0.0001-0.001[	10
[0.001-0.01[	20
[0.1-1]	35

Table 5. Comparison metrics.

Metrics	Percentage (%)	Metrics	Percentage (%)
RMSE	75.65	Relative error	4.35
R-square	70.43	Bias	4.35
MAE	26.09	NRMSE	2.61
Other	25.22	Precision	1.74
Accuracy	8.7	Error Rate	1.74
MAPE	7.83	MSE	1.74
Sensitivity	4.35	RRMSE	1.74

Table 6. Accuracy of ML models.

Metrics	Class	Percentage (%)
R-square	[0.33-0.50]	1.2
	[0.50-0.70]	3.6
	[0.90-1]	23.5
	[0.70-0.90]	61.7
RMSE	[1-5]	7.4
	0.0000000016-0.10]	29.6
	[0.10-0.50]	31.5
	[0.50-1]	31.5
MAE	[1-3]	16.7
	[0.016-0.10]	25.0
	[0.10-0.50]	25.0
	[0.50-1]	33.3

3.5.3 Model's Precision

The usage of evaluation measures is necessary for finding the best model. The performance of the most influential models was evaluated using the three-standard metrics (R-square, RMSE, and MAE). As a result, we divided these performances into intervals. For R-square, these ranges were between 0.33 and 0.99%, for RMSE between 0.0000000016 ton/ha and 5 tons/ha and for MAE between 0.016 ton/ha and 3 tons/ha. Table 6 illustrates the model performances. The performance of 61.7% of all papers that employed the R-square varied between 0.70 and 0.90 (50 out of 81), while 23.5% was between 0.90 and 1 (19 out of 27). In a work by [48] that used the SVM model to forecast rice yield, the authors found 0.33 accuracy. Just 7.45% of those who utilized the RMSE had prediction errors that were larger or equal to 1. Only 16.7% (5 out of 30) of MAE observations were greater than or equal to 1.

The best models among the others are those with high R-squares and low MAE and RMSE errors. These models can predict maize production with some degree of accuracy. However, the deviation observed for MAE and RMSE can be explained by the magnitude of the output variables used. The higher the magnitude, the higher the observed error tends to be.

3.5.6 Gaps and Perspectives

Many studies have been limited to using small data sizes to predict cereal yield, which can result in poor model performance and overfitting. Training ML models on large datasets is recommended to reduce biases. Nowadays, data accessibility and quality are major obstacles to using ML models for crop prediction. A lack of accurate and complete data can affect the reliability of predictive models. Implementing effective strategies for collecting, managing, and standardizing agricultural data is essential. These strategies could involve using advanced technologies like IoT (Internet of Things) sensors and drones to collect real-time field data. In addition, strong collaboration between researchers, farmers, and the government can promote access to quality datasets and encourage data sharing for collaborative research. By developing robust data infrastructures and promoting data transparency and accessibility, the relevance and accuracy of ML models for crop prediction could be improved. SVM and MLP have been widely used for cereal yield prediction. However, integrating emerging deep ML techniques for accurate grain yield prediction is crucial. Among these emerging techniques, CNNs and RNNs play an essential role in agriculture. Quantitative data collection can be meticulous and prone to bias. Therefore, using images to estimate yield has become a promising alternative. CNNs, designed to extract meaningful features from images, are particularly well suited to these data types. Some of the most successful variants of CNN include renowned architectures such as AlexNet, VGGNet, GoogLeNet, and ResNet.

Similarly, the use of time series data is increasing, and in this context, RNNs are emerging as recommended learning methods. Among the different RNN variants, Long Short-Term Memory (LSTM) is often favored for capturing long-term dependencies in time sequences. By integrating the suitable model according to the data type, it is possible to obtain robust and accurate predictive models that can significantly enhance agricultural decision-making. However, it is important to note that these models require extensive and high-quality databases to perform effectively. When dealing with small data for cereal production, it is also beneficial to consider the use of classical or ensemble learning techniques.

Additionally, the accuracy of a model is heavily influenced by the input hyperparameters, and optimising these hyperparameters can significantly improve the model's performance. While random search is a commonly used method for cereal prediction, Bayesian selection and grid search are also viable options that are less frequently applied. The exploration and testing of different methods for hyperparameter calibration during model training is a crucial step in ensuring the reliability and robustness of the results.

Very few factors have been studied to predict grain yields. Indeed, 43% (50 papers out of the 115) of studies have used remote sensing data, while 65% (75 papers out of the 115) have made yield predictions based on climatic characteristics. However, the literature discusses fewer other factors, such as edaphic characteristics, fertilizer levels, and water stress, which also influence yield. Thus, new data sources, such as remote sensing data, high-resolution satellite images, edaphic data, and detailed climatic data, may improve cereal yield prediction models. Also, assessment of the impact of fertilizer management on grain yield is encouraged. In addition, an analysis of the geographical scale effect on ML model accuracy is recommended to understand how spatial resolution affects results.

4. CONCLUSION

Cereal production is essential in the fight against global food insecurity. Therefore, finding the best methods to predict this crop group is necessary. This paper has focused on the ML techniques used for grain yield prediction. The papers were collected following the PRISMA method from six databases: Google Scholar, Science Direct, Scopus, IEEE, MDPI and Web of Science. The reviewed papers predicted the yield of one or more cereal crops based on ML techniques. We have also explored different factors that rely on ML based on the field of research. For example, powerful techniques such as RF, SVM, and MLP effectively predict grain yields. In addition to these techniques, LR, KNN, DT, LASSO, and CNN are also used in grain yield estimation. The performance of these techniques was evaluated based on classical metrics which were R-square, MAE and RMSE. However, access to quality data remains a significant challenge in this field. Therefore, it is crucial to implement effective strategies for collecting, managing, and ensuring the quality of agricultural data. Quality data will improve the robustness of predictive models for cereal yields and minimize crop losses, thereby boosting food security.

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The authors declare no potential conflicts of interest with respect to the research and publication of this article.

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