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A comparative study of machine learning models in predicting crop yield

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Abstract
This paper explores different machine learning techniques applied in the prediction of crop yield based on meteorological parameters. Recurrent Neural Networks (RCN), Convolutional Neural Networks, Random Forest, Decision Trees, Gradient Boosting machine (GBM) was explored. To rate the performance of machine learning models, evaluation metrics like Mean absolute error, Root mean squared error and coefficient of determination were used for decision making. The results shows that Random Forest shows high accuracy in predicting crop yield with R^2 of 0.875 for Irish potatoes and 0.817 for maize, however, for the prediction of cotton Extreme gradient boost had limited error of 0.07. Convolution neural network (CNN) was compared to traditional machine learning in the case of grading tomato and come up with a conclusion that combination of convolution neural network (CNN) with support vector machine (SVM) performed better with an accuracy of 97.54%

Keywords Machine learning, Artificial Intelligence, Internet of Things, Meteorological parameters, Smart agriculture

1 Introduction

Throughout history, civilizations have continuously adapted to changing weather patterns to ensure survival. Factors like humidity, rainfall, temperature, and wind profoundly impact daily life, prompting adjustments for optimal well-being. With the advent of Internet of Things sensors, monitoring and responding to weather conditions have become more efficient. Machine learning has revolutionized systems by enabling to learn and evolve based on experiences rather than relying solely on human programming, reducing errors. Leveraging past datasets, machine learning predicts future outcomes, with ensemble learning being a prevalent method for climate change and weather forecasting. This approach predominantly relies on historical data rather than physical processes. Weather forecasting holds diverse applications including agriculture, tourism, and aviation. Challenges include optimizing data representation and constructing reliable prediction models that capture underlying trends within extensive datasets. The availability of vast weather observation data and advancements in information and computer technologies have spurred academics to uncover hidden patterns for weather prediction. In light of escalating global warming and climatic shifts, maintaining records of weather fluctuations is crucial to mitigate potential disasters. Zhang et al. (2023) made a comparative study on machine learning models for predicting meteorological parameters and reveal that artificial intelligence and Machine Learning techniques excel in analyzing past datasets and forecasting future outcomes. Gomez and Alvarez [1] in the article machine learning based weather forecasting precision agriculture made a comparative study in in the prediction of weather parameters and impact to the crop yield and reveal that crops like maize, wheat, rice, peas, groundnuts, banana, Irish potato, and cassava have positively impacted by rainfall in the contrast to the sorghum and yam. Smith and Ahmed [2, 3] depict in the article application of machine learning models in agriculture and meteorological prediction conclude that improved weather forecasting is necessary for adaptation measures such as developing climate-resilient crop varieties, efficient water and fertilizer use. Chen et al. [4] in the article forecasting of meteorological drought using ensemble and machine learning models predicted that changes in precipitation patterns negatively impact crop productivity, particularly for cereals like maize, wheat, and sorghum.

Several studies have focused on predicting weather parameters, such as temperature, rainfall, and humidity, using various ML techniques. Zhang et al. [5] conducts a comparative study where models like Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs) outperformed traditional models, demonstrating superior accuracy in forecasting meteorological parameters across different geographical regions. Kumar and Sharma [6] in the article machine learning models crop yield based on meteorological variables depicted that Random Forest (RF) was the most effective model for predicting crop yield when incorporating both meteorological data and soil properties, highlighting the significance of integrating multiple data sources for accurate predictions. In predicting crop yield and disease outbreaks, some studies integrated additional variables, such as soil nutrition, into the predictive models. Wang and Chen [7] used RF, Support Vector Machines (SVM), and Artificial Neural Networks (ANNs) to forecast both crop yield and disease outbreaks, showing the importance of combining environmental and soil factors to improve predictive accuracy and the result of the study shows that SVM achieved a highest performance of accuracy of 0.94, precision of 0.91, recall of 0.94 and F1-score of 0.92. Similarly, Hernandez and Silva [8] introduced a multi-model fusion approach, integrating SVM, RF, and ANNs to predict grain storage temperatures, achieving higher accuracy compared to individual models. The performance of these models was typically evaluated using various metrics including Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), R-squared (R^2), and Mean Absolute Percentage Error (MAPE). These metrics provided a comprehensive evaluation of the models' predictive capabilities, with many studies confirming that ensemble methods and deep learning models consistently outperformed simpler algorithms. In another study, Brown and Miller [9] focused on using machine learning techniques in predicting soil moisture content, a crucial factor for irrigation management. By analyzing climatic data, soil properties, and vegetation indices, they applied Random Forest (RF), Support Vector Machines (SVM), and Artificial Neural Networks (ANNs) to achieve high prediction accuracy, emphasizing the efficiency of ML models over traditional soil moisture estimation methods Khan and Ahmed [10] explore the use of logistic regression, decision trees, and SVMs to predict crop disease outbreaks by analyzing historical weather data, including humidity, temperature, and wind speed. The study highlights the significance of early disease prediction in preventing crop losses and minimizing pesticide use, thus promoting sustainable farming practices. Martinez and Torres [11], developed a comprehensive machine learning framework for predicting crop yields using weather data, including temperature, precipitation, and solar radiation. They employed RF, Gradient Boosting Machines (GBM), and K-Nearest Neighbors (KNN) for accurate crop yield forecasting, with the Random Forest model showing exceptional performance in terms of prediction accuracy. Deep learning models have proven valuable in forecasting agricultural outputs based on weather conditions. Nwachukwu et al. [12] integrate satellite imagery, specifically the Normalized Difference Vegetation Index (NDVI), with environmental factors like precipitation and temperature. Random Forest (RF), SVM, and ANNs models were employed to predict crop yields with high accuracy, highlighting how remote sensing technology can revolutionize precision agriculture by providing real-time insights into crop health and growth patterns. Hoque et al. [13, 14] took a unique approach by integrating meteorological data and pesticide usage records into crop yield prediction models. They utilized Gradient Boosting, K-Nearest Neighbors (KNN), and Multivariate Logistic Regression to improve prediction accuracy, with the Gradient Boosting model achieving exceptional R^2 values of 0.9999 a higher input for yield variability. Burhan [15] applied a similar methodology by combining weather data and pesticide in the improvement of crop yield forecasts with emphasis on wheat, barley and maize. Lin et al. [16] represents a state-of-the-art deep learning approach to crop yield prediction that accounts for both short-term weather variations and long-term climate change. Multi-Modal, Spatial, and Temporal Transformers, demonstrated superior predictive performance across multiple U.S. counties, emphasizing the importance of integrating multiple data sources and modeling spatial–temporal dependencies for accurate crop yield predictions, key results for soybean with multi-modal pre-training of RMSE 3.9, R^2 of 0.843 and correlation of 0.918. Finally, Mohanty et al. [17] demonstrate the power of machine learning for weather forecasting in precision agriculture. Using models like Random Forest (RF), SVM, and ANN, comparing the effectiveness of these models in predicting meteorological parameters essential for agriculture, such as temperature, humidity, and precipitation. This paper explores the contribution of machine learning models in agriculture with consideration of meteorological parameters to improve crop yield and productivity. The researcher considers quality publication from 2018 to date with the perspective of selection of a specific machine learning which could be consider in the scope of research work to be undertaken. This paper is organized as follow: In Sect. 2 review of literature, Sect. 3 methodology used in papers selection as per the area of application, Sect. 4 papers analysis. The conclusion is made in Sect. 5.

2 Motivation

As per the global trend, in 2050, the world population is expected to be 9.2 billion. In that aspect there is need to ensure food security for all. We cannot ignore that climate variability has negative impact to agriculture and at the end affect productivity and be the major cause of hunger. We cannot also ignore that technology is used to respond to the problem we are facing, in that line, many machine learning techniques have been applied for solution, however, each geographic area has its own reality. A contextualization of machine learning models in the context of Rwanda for the future work.

3 Contribution

The main contribution in this study is highlighted as follows:

A. BOBO MAFREBO Lionel, Play a key role in the conceptualization in regard to the area of research and future development of prototype. B. Richard Musabe, Play key role in the review of the proposed model C. Omar Gatera, review and validate the concept used D. Twizere Celestin, Review the final manuscript

- Perform comprehensive literature review for different machine learning models applied in agriculture with consideration of meteorological parameters;
- A detailed analysis and study based on research questions;
- Challenges identification highlighted and future research direction proposed.

4 Section II. Related study

The core objective of this section is to explore the contribution of machine learning techniques in agriculture vis a vis to climate variability reviewed in different articles. Meteorological parameters affecting crop yield and productivity in agriculture practices considered in this study are temperature, rainfall, humidity, air pressure and soil acidity. Various studies had demonstrated that application of machine learning associated with artificial intelligence, Internet of things contribute in the response to climate variability by proposing innovative solutions in crop yield, smart irrigation and other best practices if consider only agriculture sector. Recent studies have explored various machine learning techniques, including Random Forest Regression, Deep Neural Networks (DNN), Ensemble Methods, and deep learning architectures like Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), for predicting crop yields based on weather variables, remote sensing data, and other relevant factors. Random Forest Regression is mostly used in image classification and regression tasks. It has the ability to produce accurate outcome. Kuradusenge et al. [18, 19], depicted that Random Forest algorithm outperformed Polynomial Regression and Support Vector Regression for predicting the yield of maize and Irish potatoes. Figure 1 provide a structure for Random Forest Regression.

Mahankale et al. [20] reported that deep neural networks model performed significantly better than other models like MARS, RF, SVM, ANN, and ERT for predicting

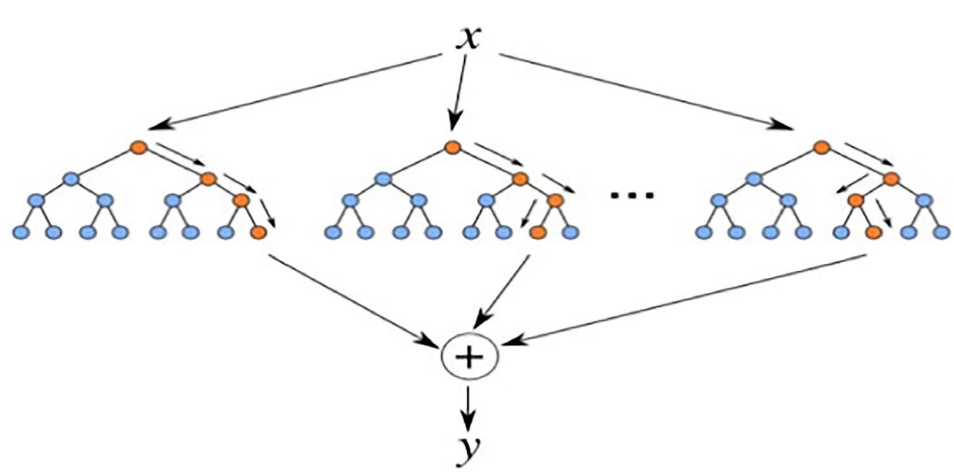

Fig. 1 Structural representation of the random forest regression model

maize yield based on weather variables and remote sensing data. Figure 2 provide sequence structure of Neural Networks model.

Li et al. [21] suggested to explore ensemble methods or hybrid models that combine multiple algorithms to improve accuracy in weather forecasting and yield prediction. Figure 3 depict structure for the ensemble model.

Convolutional Neural Networks (CNN) model is convenient to users due to its flexibility and it is composed of hierarchical features from visual inputs. The design is composed of different parameters such number of filters and filter sizes. Figure 4 provide a structure of the Neural Networks.

Recurrent Neural Networks model is determined by the inputs at the current time step and the hidden state from the time step prior. Algarni [22], Elghamrawy [23] mentioned the potential of deep learning techniques like CNN and RNN for crop disease prediction, feature extraction, and time-series forecasting, which could be useful for incorporating weather data and predicting yield. Ramesh and Kumaresan [24] demonstrates that hybrid models, such as CNN-DNN and RNN, outperformed traditional models, offering better predictive power, especially under adverse climatic conditions. Li et al. [21] introduced a hybrid weather forecasting model combining Spatial–Temporal Attention Networks and Multi-Layer Perceptron (E-STAN-MLP), achieving better predictive accuracy for meteorological parameters than traditional methods. This section provides literature review on the contribution on the identified ML techniques in the prediction of meteorological parameters to improve crop yield prediction in smart agriculture. Manjula et al. [25] developed ML models for predicting crop yields, integrating meteorological data and soil properties. The study revealed that adding soil factors, such as pH and organic carbon content, to weather data significantly improved yield predictions for rice and wheat crops. Random Forests (RF) were identified as the most accurate model for both short-term and long-term yield forecasts. Sharma et al. [26, 27] introduces an integrated approach that combines weather data, soil nutrition, and historical disease records to predict both crop yields and disease outbreaks. The study highlights the importance of these combined variables for achieving highly accurate predictions, with Random Forest (RF) demonstrating the best performance across both tasks. Chouhan et al. [28, 29] develop a multi-model fusion approach for predicting temperature variations in stored grain. Using machine learning models such as ANN, SVM, and

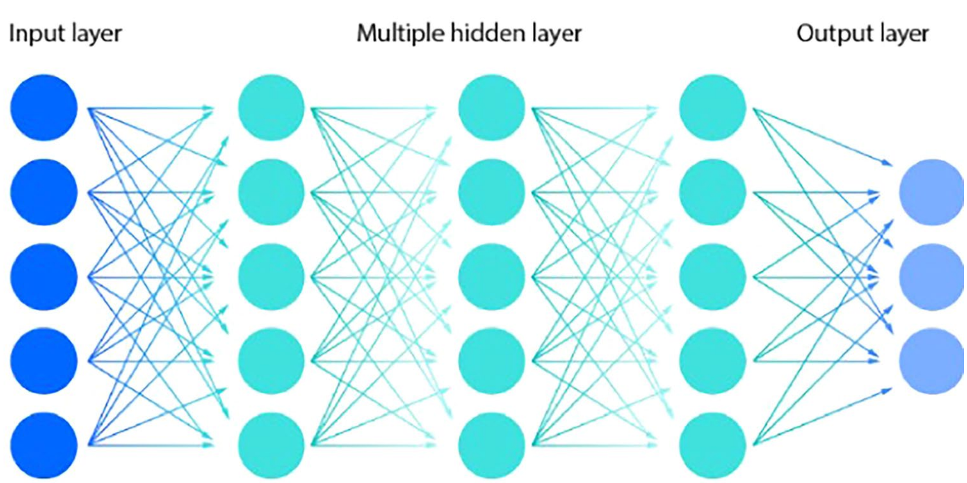

Fig. 2 Sequential architecture of the neural network model

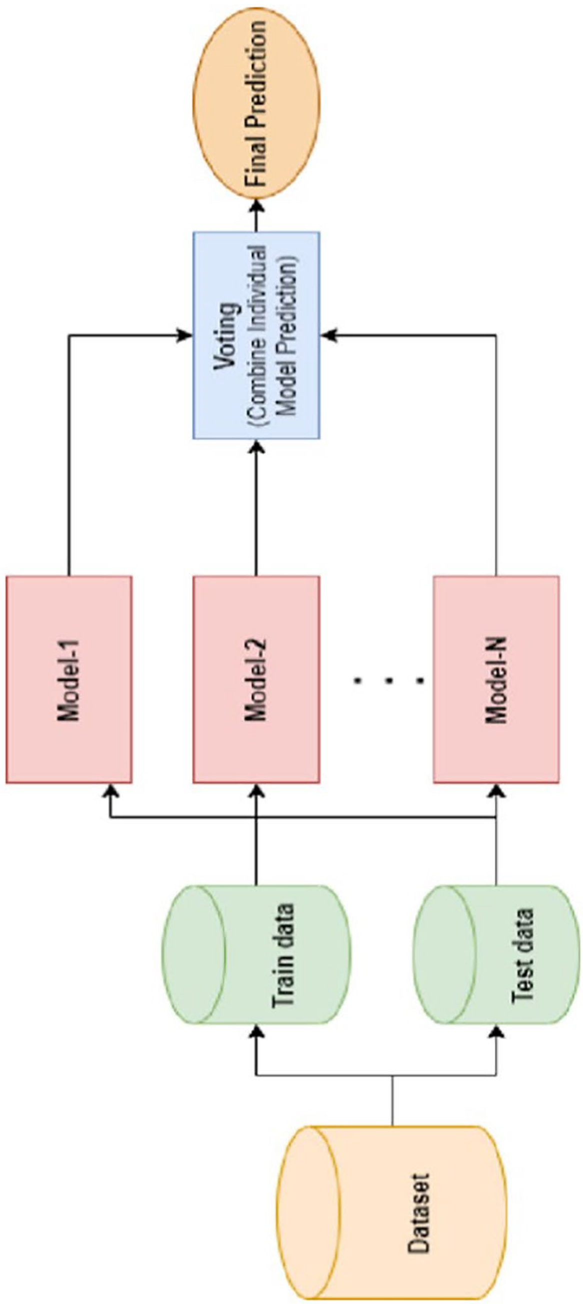

Fig. 3 Schematic illustration of the ensemble model architecture

Decision Trees, the fusion of these models provided superior predictive accuracy compared to individual models, making the approach highly effective for managing grain storage temperature and preventing spoilage. Kumar et al. [30–32] explore AI-powered weather forecasting to optimize precision agriculture. The study uses machine learning algorithms like SVM, RF, and deep learning models (CNN, RNN) to predict critical weather parameters, including temperature, humidity, and rainfall. The research found that deep learning models, especially RNNs, excelled in capturing temporal weather patterns, improving forecasting accuracy. Gómez et al. [33] develop ML models to predict soil moisture content using meteorological data and soil characteristics. By applying RF, SVM, and ANN, they found that RF and ANN outperformed SVM in terms of accuracy, showing that ML significantly optimize irrigation practices and reduce water wastage, especially in water-scarce regions. Anderson et al. [34] used machine learning algorithms like Decision Trees, Logistic Regression, and Neural Networks to predict crop disease outbreaks based on meteorological data. The study highlights the importance of weather variables such as temperature and humidity in disease prediction, with Neural Networks achieving the highest prediction accuracy for both disease outbreaks and their severity. McKinney et al. [35] develop a machine learning framework for predicting agricultural yields using weather data. Support Vector Machines (SVM), Random Forest (RF), and Gradient Boosting Machines (GBM) were used to predict crop yields. The findings shows that Random Forest (RF) provided the highest accuracy, highlighting the importance of integrating weather data for accurate crop yield predictions. Zhan et al. [36] apply deep learning techniques to predict agricultural crop yields using meteorological data. The study demonstrates that a Deep Neural Network (DNN) model outperformed traditional models like SVM and RF, showing the potential of deep learning in capturing non-linear relationships in large datasets, improving crop yield prediction accuracy. Rojas et al. [37] proposed an integrated approach for crop yield prediction by combining remote sensing data with machine learning models. The study shows that combining vegetation indices from satellite imagery (NDVI, EVI) with weather data significantly improved prediction accuracy, surpassing traditional models that used only one data source. This integrated approach is valuable in precision agriculture and climate adaptation. Kumar et al. [30–32], explore machine learning techniques for forecasting agricultural drought using meteorological data. The study considers SVM, Artificial Neural Networks (ANNs), and RF, with SVM demonstrating the best predictive accuracy. Thompson et al. [38] investigated the use of machine learning for predicting both meteorological variables and agricultural outputs. From the proposed machine learning models SVM, RF, and ANN,the Artificial Neural Networks performed better in capturing complex relationships between weather data and crop outcomes. Peterson et al. [39], introduced a machine learning framework for predicting agricultural yields based on weather data. Ensemble models, including Random Forest (RF) and Gradient Boosting Machines (GBM), outperformed traditional statistical models. Zhang et al. [40] developed an AI-based framework for predicting soil moisture and evapotranspiration (ET). Using Convolutional Neural Networks (CNNs) and Long Short-Term Memory networks (LSTMs), the study demonstrates that AI models provided superior prediction accuracy compared to traditional methods. The approach is crucial for precision agriculture, irrigation management, and climate adaptation strategies. Sharma et al. [41] apply machine learning models to predict agricultural yield and weather variables, such

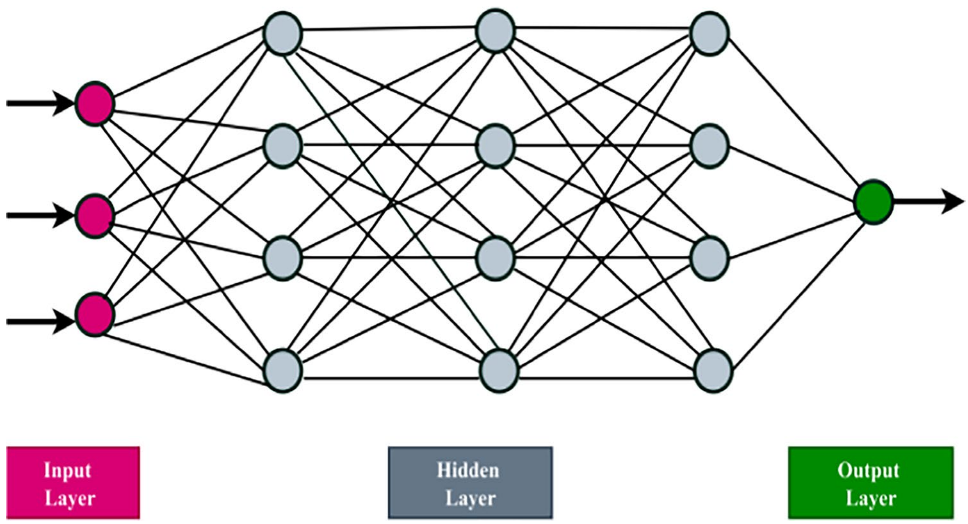

Fig. 4 Structural representation of the neural network architecture

as temperature and rainfall. The study compares SVM, RF, and GBM, concluding that GBM was the most accurate model for predicting yield, underlining the significance of incorporating both weather and agronomic factors in agricultural prediction. Johnson et al. [42] investigated the use of machine learning models to forecast crop yield by integrating weather data and soil characteristics. The study highlighted that Random Forest (RF) provided the best predictions compared to other models, showcasing the importance of integrating both weather and soil data to improve crop yield forecasts. Williams et al. (2024) explore the application of machine learning models for predicting drought conditions using meteorological and soil data. The study applied Random Forest (RF), Support Vector Machine (SVM), and Gradient Boosting Machines (GBM) to forecast droughts, with GBM outperforming other models. Liu et al. [43–45] focus on predicting agricultural yields in response to climate change. Using machine learning models such as Random Forest (RF), Support Vector Regression (SVR), and Artificial Neural Networks (ANN), the study examined the impact of climate change on wheat and maize yields. ANN provided the most accurate predictions, offering a robust approach for forecasting agricultural productivity under future climate scenarios. Carter et al. [46] propose a deep learning-based method for predicting wheat yield using Convolutional Neural Networks (CNN) combined with climate data. By incorporating climate variables and remote sensing imagery, the CNN model significantly outperformed traditional models, showing the potential of deep learning for improving yield predictions and climate adaptation strategies (Table 1).

Hassan et al. [49] shade light in comparing convolutional neural network and the tradition machine learning in the prediction on sorting and grading tomato,NUDIA Jetson TX1 was used to create image dataset. A combination of convolutional neural network (CNN), Sector vector machine (SVM) and the Random Forest compare to K-nearest neighbors (K-NN) in the prediction, the result shows that hybrid model CNN-SVM outperformed and achieve an accuracy of 97.54% in categorization of tomato as ripe, unripe, old or damaged. Figure 5 highlight the crop yield prediction process using machine learning.

Table 1 Comparative performance metrics of machine learning in predicting crop yield

Study	Employed machine learning	Parameters considered	Performance
Joshi et al. [47]	Random forest, support vector machine	Precipitation, temperature and solar radiation in predicting level rice yield	SVM demonstrate an accuracy of R^2 0.82, MAE 0.29 and MAPE 0.16
Hoque et al. [14]	GBM, multivariate logistic regression and K-nearest neighbors	–	GBM perform with an accuracy of R^2 of 0.99, K-nearest neighbors 0.98.59 and multivariate logistic regression of 0.96.78
Syed Tahseen et al. (2024)	Gradient forest extreme gradient, extreme gradient boost model (XGB)	Cotton production	soil accuracy of 0.05 RMSE compare to 0.07 of accuracy using the extreme gradient boost model (XGB)
Sight et al. (2020)	Multivariate regression models	Climate data, soil health	R^2 was 0.94 and margin of error (ME) of 0.03
Hu et al. [48]	Gaussian Naïve Bayes (GNB), support vector machine (SVM), artificial network networks	Evatranspiration	KNN model is more accurate at the rate of 92% and reduce the root mean squared error (RMSE) by 16% and the mean absolute error by 3%
Kuradusenge et al. [18, 19]	Ensemble models	Irish potatoes, Maize, rainfall and temperature	RF has high accurate predictions for crop yields with R^2 of 0.875 for Irish potatoes and 0.817 for maize. The RMSE was 510.8 for potatoes and 129.9 for maize

Thomson et al. (2024) made a comparison of three regression models including Random Forest, Xtreme gradient boosting regression and absolute shrinkage and selection operator (LASSO) to examine effect of seeding plan on crop yield; the results show that LASSO achieved the highest performance R^2 of 0.93 and the average predicted yield 260.54 g/m^2. Results of compared machine learning models is depicted in Fig. 6 showing the actual and predicted grain yield.

Admasu et al. [50] investigated the use of machine learning models for predicting meteorological parameters relevant to agriculture. Findings demonstrated that hybrid models that combine multiple algorithms offer improved prediction accuracy, making them valuable for agricultural decision-making. Lee et al. [51] focused on forecasting weather conditions crucial for crop growth, such as temperature and rainfall, using machine learning algorithms. The study compared k-Nearest Neighbors (k-NN), Artificial Neural Networks (ANN), and Gradient Boosting Machines (GBM), with GBM proving to be the most accurate in predicting weather parameters essential for agriculture.

The integration of IoT technologies and machine learning (ML) models continues to offer innovative solutions to various challenges in agriculture, particularly in the areas of crop monitoring, climate adaptation, and resource management. Isaac Rutemberg (2021) demonstrates how AI can enhance predictive models related to climate risks such as floods, droughts, and migration patterns. The study emphasized the importance of adapting AI tools to African contexts for climate change adaptation, particularly in agriculture where AI models can predict crop yields under varying climate scenarios. Kundar et al. (2019) present an IoT-based smart technology to support farmers in Rwanda, particularly in Kayonza District, by providing real-time weather data. The proposed system leveraged IoT sensors to collect environmental data such as temperature and humidity, enabling farmers to make better decisions regarding crop management. The study highlights the potential of IoT in enhancing farm productivity and mitigating climate-related challenges. Afreen and Bajwa [52], develop an IoT-based real-time intelligent monitoring system for cold storage, focusing on the storage of perishable fruits and

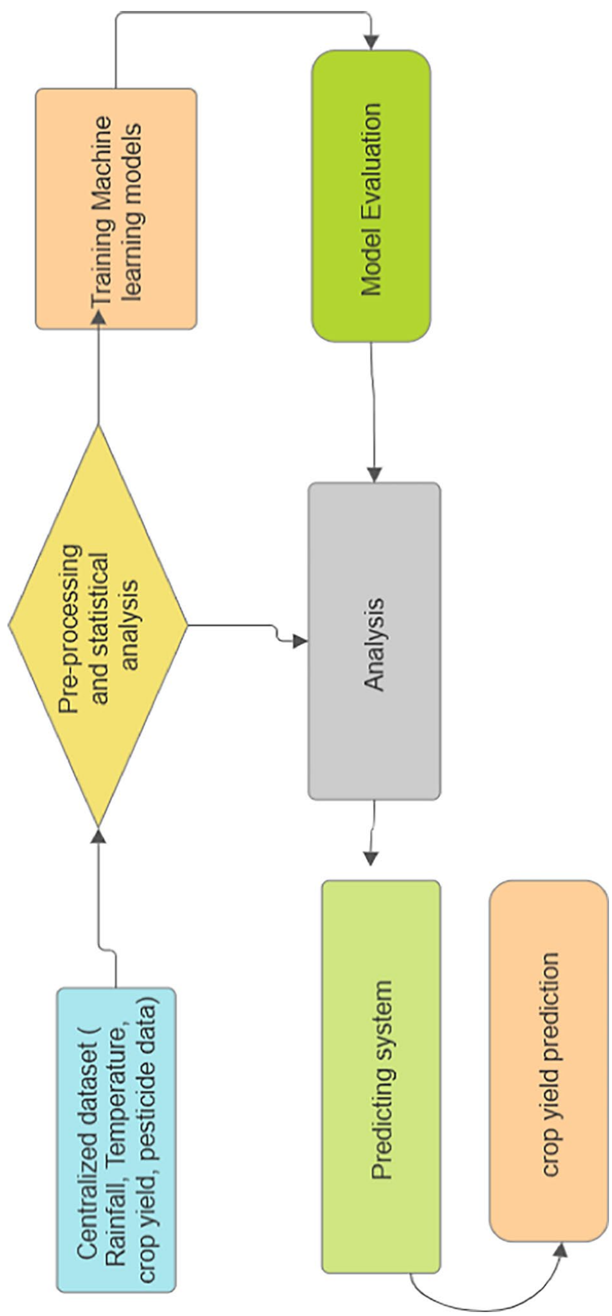

Fig. 5 Conceptual framework illustrating crop yield prediction through machine learning

vegetables (FVs). The system monitored key environmental parameters such as temperature, humidity, and gas concentrations, notifying personnel when any parameter exceeded dangerous limits. The proposed system used an Artificial Neural Network (ANN) model for predictive analysis, achieving high accuracy in forecasting the storage conditions and improving the shelf life of stored produce, the results shows that ANN having accuracy of 99% with forward propagation, compress sending of 95.8%. Rahut et al. [53] propose a smart weather monitoring system using IoT to measure parameters such as temperature, humidity, wind speed, and UV radiation. The data collected from sensors was transmitted to a cloud-based platform, where it was displayed in real-time on a web interface. This system is beneficial for meteorological departments, weather stations, and agriculture, as it provides accurate weather data remotely and cost-effectively. Sharma and Prakash [54] developed a real-time weather monitoring system using IoT in the Gorakhpur region. This system used multiple sensors to track temperature, humidity, rainfall, and pressure, and display the data on a web server for easy access. The study underscores the importance of real-time weather data in supporting agricultural decision-making, especially in regions prone to extreme weather conditions. Kodali et al. (2024) focus on IoT-based weather monitoring for greenhouses, proposing a system to monitor critical parameters such as temperature, humidity, light, and air quality. The system provided real-time data analysis, enabling automated responses such as adjusting environmental conditions within the greenhouse to ensure optimal crop growth. This study shows how IoT can improve efficiency and productivity in controlled farming environments like greenhouses. Kumar and Savaridassan [55] examine the use of IoT in hydroponic systems to accelerate plant growth. The system monitored environmental parameters such as temperature, pH levels, and nutrient concentrations to optimize plant growth without soil. Growth rate measured in cm/week showed an increase of 15–20% compared to controls, nutrient efficiency improved by 18% and the sensor accuracy at 95%. Menon and Prabhakar [56] develop a Smart Agriculture Monitoring Rover for small-scale farms, the proposed system uses GPS and GSM for data transmission, providing farmers with real-time monitoring capabilities,based on the results, the soil moisture sensor was tested against manual measurement and provide an accuracy of 92% and navigation precision of ± 5 cm; 92% of farmers reported the system to be easy for use and improve the irrigation system. Sirisha and Sahitya (2021) explore the integration of IoT in precision agriculture, focusing on smart irrigation systems powered by Support Vector Regression (SVR). The system predicts soil moisture levels and evapotranspiration, scheduling irrigation processes accordingly. This study demonstrates how IoT and ML can optimize water usage in agriculture, improving crop yield while conserving resources, the result demonstrated that water usage reduction at a rate between 20 and 25%, RMSE and MAE prediction of accuracy of 0.03. Mishra et al. [57] explore the use of IoT-based smart irrigation systems, integrating water level indicators and logistic regression models for automated irrigation. This system collects real-time data on soil moisture, crop type, and weather conditions, offering significant improvements in the efficiency and accuracy of irrigation, especially in areas facing water scarcity, the results show accuracy, precision and recall all above 90%. Kashyap et al. [58] propose a smart real-time weather forecasting system using IoT sensors and wireless communication to collect and analyze meteorological data. The system is cost-effective and provides accurate predictions for temperature and humidity, critical for agriculture. It helps

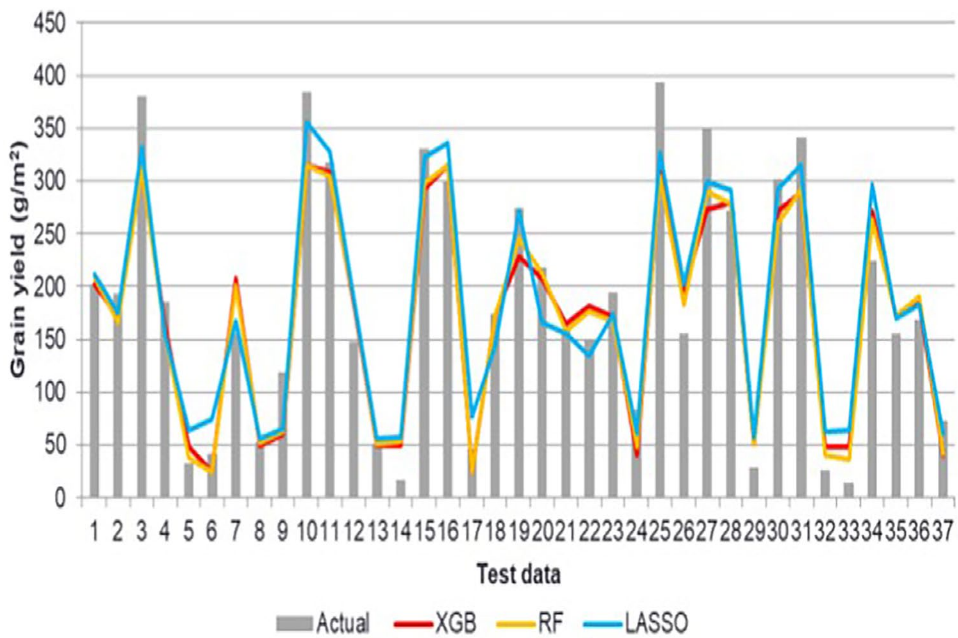

Fig. 6 Visualization of actual grain yield against machine learning prediction

farmers make informed decisions to optimize crop yields and minimize damage from unpredictable weather patterns, additional to that the forecast accuracy evaluated via MAPE was 8% and the latency in data was below three seconds. Sivakumar and Nanjundaswamy [58] introduced an IoT-based weather monitoring system designed for real-time weather and environmental data collection. The system offers predictive weather capabilities by using multiple sensors to measure temperature, humidity, and air pressure. The system's cloud-based architecture allows easy data access and forecasting, which is particularly useful for agriculture, mining, and weather stations. Dos Santos et al. [59] presented Agri Prediction, a proactive IoT model for anticipating agricultural problems using LoRa technology and the ARIMA prediction model. The framework uses environmental sensors to monitor soil moisture and temperature, and by predicting future trends, it allows farmers to take preventative actions. The system demonstrates an increased crop productivity, particularly for arugula cultivation,the early detection problem on crop was reduced by 30% and the prediction of disease outbreaks with 87% precision. Mudgil [60], propose an IoT-based smart weather monitoring system that tracks temperature and humidity using a Particle Photon IoT board. The setup provides real-time weather data, enabling farmers to optimize their irrigation practices and improve crop yields. The system's low cost and ease of installation make it suitable for wide-scale adoption in agriculture. The sensor data accuracy was 95%. Ara et al. [61] developed an energy-efficient IoT-based smart farming system for disease prediction. Their hybrid model, combining K-means clustering and Adaptive Mud Ring optimization, efficiently selects cluster heads and optimizes energy consumption. The system predicts diseases based on data collected by sensors, improving crop management and reducing pesticide usage. The results of the study indicated disease prediction accuracy at a rate of 90%, energy consumption reduced at a rate of 35%. Sharma and Sharma [62], implemented a smart weather reporting system based on the Blynk app for agriculture. This IoT system collects and reports real-time weather conditions, including temperature, humidity, and wind speed, aiding farmers in making timely decisions regarding irrigation and crop protection. Shaikh et al. [63], examine AI's role in smart agriculture, emphasizing its use in soil and irrigation management, weather forecasting, and disease prediction. The review application of AI algorithms, particularly deep learning, which has shown superior performance in handling complex agricultural data compared to traditional machine learning methods. The paper also discussed future trends and challenges in AI adoption for smart agriculture. Nyakuri et al. [64] develop an AI-based real-time weather condition prediction system integrated with IoT for optimized irrigation and fertigation in agriculture. The incorporated Fuzzy Inference Systems (FIS) and machine learning algorithms, helps manage water and fertilizer resources efficiently, leading to significant resource savings and increased crop yields. Javaid et al. [65] explored AI's potential applications in agriculture, highlighting its use in pest control, soil health monitoring, and crop yield prediction. The integration of AI with IoT devices like drones and sensors to monitor crop conditions, optimize irrigation, and predict yields. This paper emphasizes the importance of AI in addressing challenges such as climate change, labor shortages, and the need for increased food production. Ashraf and Akanbi [66], discuss the integration of IoT, cloud computing, and AI in sustainable agriculture. The framework supported crop management and yield forecasting by utilizing IoT sensors to monitor soil and weather conditions. The data collected is processed in the cloud, where AI models predict crop yields and detect potential diseases, optimizing resource utilization and reducing waste in agricultural practices. Singh et al. [67], introduce a LoRa-based intelligent system for soil and weather condition monitoring. This system, designed for precision agriculture, utilizes IoT sensors to monitor key parameters like soil moisture, temperature, and humidity. The system then feeds data to the cloud, where machine learning models are applied for irrigation scheduling and weather prediction, offering a cost-effective solution for urban farming in smart cities. Majumdar et al. [68] reviewed IoT-based systems for promoting Agriculture 4.0, focusing on weather monitoring, yield prediction, and hardware cost analysis. The study revealed that temperature and humidity are the most commonly monitored parameters in IoT systems for agriculture, and they emphasized the need for more affordable sensors to improve the scalability of these systems. Colombo-Mendoza et al. [69] propose a smart farming system that combines IoT sensors with data mining techniques for crop production prediction. The method analyzes climate and crop production data from various sources, including IoT sensors and government databases, to predict crop yields. The system was tested using historical data from Puebla, Mexico, demonstrating the potential of IoT and machine learning in small-scale farming.

Jagatheesan and Janaki [70], design an IoT-based weather monitoring system for smart farming. The system collected environmental data using low-cost sensors and transmits it to a cloud platform, where AI algorithms predict the most suitable conditions for crop growth. This approach helps farmers optimize water usage and improve crop yield through real-time weather monitoring. Satish et al. [71], explore AI's role in predicting climate change impacts, focusing on weather projection and ecological surveillance. The study highlights the importance of AI technologies such as machine learning and neural network's ability to improve the accuracy of climate models, helping predict extreme weather events, sea-level rise, and ecosystem shifts. This research shows how AI can be leveraged to mitigate the impacts of climate change on agriculture. Dhar et al. [72], investigate the use of AI in addressing climate change to achieve environmental justice. The work proposes AI as a tool for addressing the environmental inequalities experienced by developing countries, particularly in agricultural contexts. Pandow et al. [73] examine the use of AI in climate finance, focusing on its impact on operational efficiency, resource allocation, and sustainable investment.

Duklan et al. [74, 75], discuss AI's role in climate change estimation, focusing on forecasting energy consumption in buildings and assessing the environmental impact of various sectors. Ashraf and Akanbi [66], discuss the integration of IoT, cloud computing, and AI can enhance sustainable agricultural practices, particularly in crop management and yield forecasting. IoT sensors monitor environmental conditions in real-time, transmitting data to cloud platforms where AI models predict crop yields and detect diseases, optimizing resource usage and improving sustainability in agriculture. Singh et al. [76], focus on the role of LoRa-based IoT systems for monitoring soil and weather conditions in smart cities. The research introduces intelligent irrigation systems that leverage IoT for soil moisture, temperature, and weather data, utilizing machine learning algorithms for irrigation scheduling and weather prediction. The approach aims to provide a cost-effective, sustainable solution for urban agriculture. Majumdar et al. [68], explore the integration of IoT technologies with agriculture 4.0, reviewing the use of weather monitoring and yield prediction systems. The study shade light on the importance of selecting appropriate IoT sensors for efficient agricultural data collection and the cost-effectiveness of various systems, noting that temperature and humidity were the most commonly monitored parameters. Colombo-Mendoza et al. [69], develop a smart farming system using IoT sensors and data mining techniques for crop production prediction. The system integrates various data sources, including climate and soil data, to predict crop yields using machine learning models. The system was validated using historical data from Puebla, Mexico, showcasing its potential for small-scale farmers. Jagatheesan and Janaki [70], propose a big data analytics approach to climate-smart agriculture, aimed at predicting environmental changes and supporting farmers' adaptation to climate challenges. Jagatheesan and Janaki [70] present an IoT-based real-time weather monitoring system for smart farming. The system uses low-cost sensors to collect environmental data such as temperature, humidity, and soil moisture, which is then analyzed on a cloud platform to optimize irrigation practices and improve crop yield predictions. Satish et al. [71] review the role of AI in predicting climate change impacts. The study gave light on machine learning algorithms application, particularly in climate simulation and weather projection, which improve the accuracy of climate models, predicting extreme weather events and assessing their impact on agriculture. Duklan et al. [74, 75] investigates the dual role of AI in both mitigating and adapting to climate change. The researcher emphasized AI’s contributions to climate change estimation, particularly in energy consumption prediction for buildings, and its potential to aid in the development of effective climate change mitigation policies.

Liu et al. [77] propose, integrates the Weather Research and Forecasting (WRF) model with Backpropagation Neural Networks (BPNN). This model was designed to enhance the accuracy of weather forecasts, particularly for temperature and mixing ratio profiles. The results showed that the WRF-BPNN model outperformed the traditional WRF model, demonstrating the potential of combining numerical weather models with AI to address uncertainties in meteorological predictions. Scher and Messori [78] explored ensemble methods in neural network-based weather forecasts. The study demonstrated that transforming a deterministic neural network into an ensemble forecasting system improved the forecast's accuracy. This research highlights how neural networks can be leveraged for probabilistic weather forecasting, offering better uncertainty measures and improved prediction skills compared to traditional models. Wang and Abdelrahman [79] developed an AI-enabled flood prediction system by integrating data from local sensors and third-party weather forecasts. The system designed for real-time predictions, successfully incorporated machine learning algorithms to predict flooding risks based on environmental conditions, offering a critical tool for disaster management in vulnerable areas. Weyn et al. [80], demonstrated the use of deep convolutional neural networks (CNNs) for weather prediction. The models, trained solely on past weather data, showed that CNNs could outperform traditional weather forecasting methods, particularly in predicting significant atmospheric changes. The work indicated that machine learning, particularly deep learning, could be a promising tool for improving weather forecasts. Dewitte et al. [81], discuss the role of AI in revolutionizing weather forecasting, climate monitoring, and decadal predictions. By applying machine learning techniques to large datasets, the study highlighted the potential of AI to reduce human effort, optimize computational resources, and enhance forecast quality. Ibrahim et al. [82] applied machine learning techniques to predict potato diseases in Nigeria's smallholder agricultural areas. The study utilized remote sensing data and machine learning models like Random Forest to predict disease outbreaks, the study revealed that Random Forest predict disease incidence between 72 to 96% of potato crop between 2019 to 2021. Huang et al. [83] proposes a real-time weather monitoring system using city buses equipped with IoT sensors. The system used machine learning algorithms like LSTM and MLP, successfully forecasted weather conditions, enhancing the accuracy and coverage of weather predictions in urban areas. The integration of mobile platforms and IoT technology provided a cost-effective solution for localized weather prediction. Bochenek and Ustrnul [84] review the applications of machine learning in weather prediction and climate analysis. The study pointed out the future potential of machine learning in meteorology, particularly in improving the accuracy of climate models and weather predictions. Cuc et al. [85], described an IoT-based weather monitoring system that combines IoT sensors with machine learning models to predict weather conditions. The study demonstrated that the use of AI in analyzing real-time data from temperature and humidity sensors, helping improve weather prediction accuracy through AI algorithms like linear regression. Fowdur et al. [86] introduced collaborative machine learning-based weather forecasting system that used data from multiple predictor locations. The study showed that collaborative forecasting, using multiple weather stations and various machine learning algorithms, such as multiple linear regression and convolutional neural networks, could improve the accuracy of weather predictions by reducing prediction errors. Zeng [87], discussed the importance of AI in climate resilience, highlighting how machine learning is transforming weather forecasting and climate prediction. The study highlighted that AI enhances the accuracy and speed of climate predictions, making it a critical tool for agriculture, disaster preparedness, and long-term sustainability. Paudel et al. [88] developed a machine learning-based approach for large-scale crop yield forecasting. The approach highlighted the modularity and reusability of machine learning models, which can be adapted for different crops and regions with minimal configuration changes, the study normalized early season predictions 30 days post planting and also season forecast (Table 2).

Singh and Sharma (2024), emphasizes the role of AI integration, and calls for strategic improvements to close existing research and implementation gaps. demonstrates that the TCRM model delivers highly accurate, cloud-based crop recommendations tailored to local conditions, making precision agriculture accessible to remote and resource-limited farmers. With impressive evaluation metrics, it shows promise as a scalable solution for sustainable farming.

Suarez et al. [97] focused on early-season yield forecasting for citrus crops in Australia. Using time-series remote sensing data, their machine learning models predicted yield with high accuracy. The study demonstrated the effectiveness of SVM algorithms in capturing non-linear relationships between environmental factors and crop yield, highlighting how machine learning can enhance pre-harvest forecasting. Ajith et al. [98] conducts a systematic review of statistical and machine learning models used for location-specific crop yield prediction. The proposed models like Artificial Neural Networks (ANN) and Support Vector Regression (SVR) performed best due to their ability to handle complex, non-linear relationships between weather factors and crop yield, providing valuable insights for localized decision-making. Mahmood et al. [99] explore the integration of ML, AI, and IoT into agricultural systems to improve yield prediction and resource management. The study highlighted the importance of sensors and data analytics in enabling more efficient farming practices, particularly in crop disease prediction and soil condition monitoring.

Liu et al. [43–45] explore machine learning models for crop yield prediction and nitrogen status estimation in precision agriculture. The study highlights the role of machine learning models in reducing fertilizer use by accurately predicting nitrogen levels in soil,

Table 2 Contribution of Machine learning in crop yield prediction in consideration of various parameters

Study	Employed machine learning	Parameters considered	Performance
Lee et al. [89]	Ensemble models	Earth observation data to forecast maize for Sub-Saharan (Africa)	EO features improve the accuracy where NSE > 0.6 and MAPE < 20%
Suaza-Medina et al. [90]	Random forest and gradient boosting	Normalized Difference Vegetation Index (NDVI) and climatic data	The model demonstrates classification accuracy of 92.1%
Imade et al. [91]	Random Forest, AdaBoost Regressor and CNN	Prediction of agriculture yields	CNN achieved high accuracy of F1 score of 99%, boost regressor had a lowest error of MAE 0.22, RMSE of 0.31. The Random Forest provide a strong R^2 of 0.89
Chlingaryan et al. [92]	Ensemble models	Nitrogen estimation	The hybrid systems boost yield in the range between 12 to 17% and reduce fertilizer between 10 to 14%
Pathania et al. [93]	RF, SVM, XGBoost	Rainfall forecasting	Ensemble models (XGBoost, RF) outperformed other methods with R^2 of 0.99
Bansal et al. [94],	Ensemble models	Soil parameters	The Integrity heterogeneous of soil was demonstrated by achieving MAE of 0.82 and RMSE of 0.98t/ha
Singh and Sharma [95]	TCRM model	Cloud-based crop	The quantitative results provide an accuracy of 94%, Precision 94.46%, Recall 94%, F1 93.97%, CV 97.67%
Shahhosseini et al.[96]	Ensemble models	Prediction of corn yield	The relative root mean square error (RRMSE) reached 7.8% and the mean bias error (MBE) was considered as lowest at – 6.06bu/acre

contributing to more sustainable agricultural practices. Khan et al. [100] conduct a case study in Tennessee, where machine learning was used for smart weather forecasting. The study demonstrated that ML models could significantly improve the accuracy of weather predictions, allowing farmers to make informed decisions on crop management and irrigation scheduling. Li et al. [101] propose an ensemble method combining spatial–temporal attention networks with Multi-Layer Perceptions (MLP) for weather forecasting. The model effectively handled the complexities of weather data, offering superior prediction performance compared to traditional methods, which is particularly useful in agricultural planning and weather-dependent industries. Ayaz et al. [102], explore the integration of IoT and machine learning in agriculture, particularly focusing on how IoT sensors help in real-time crop monitoring, pest management, and irrigation optimization. The work showed that IoT-based smart agriculture systems enhance farm productivity by providing timely insights into environmental conditions. Murugan et al. [103], introduce an AI-based weather monitoring system using IoT and deep learning algorithms. The system help to predict weather patterns, providing valuable information for agricultural practices, particularly in regions prone to erratic weather conditions Sharma et al. [104], conducts a review on the use of machine learning applications in precision agriculture, focusing on various aspects like crop monitoring, soil analysis, irrigation, and disease management. The research highlighted how AI models, integrated with remote sensing technologies, can lead to more efficient farming practices. Jabed et al. [105] review machine learning and deep learning approaches for crop disease prediction. The research emphasized on the growing role of deep learning techniques like Convolutional Neural Networks (CNN) in accurately detecting plant diseases and improving disease management in agriculture. Benos et al. [106] review the advancements in machine learning for agricultural management, focusing on crop management, soil monitoring, and livestock management. The study revealed that AI can optimize agricultural productivity and sustainability, particularly through resource management and precision farming. Mohyuddin et al. [107] evaluates various machine learning approaches in precision farming, highlighting the integration of autonomous vehicles and drones for efficient planting, irrigation, and harvesting. The work emphasized how these technologies can increase productivity while minimizing environmental impact. Wang et al. [108] review the integration of remote sensing and machine learning in precision agriculture. They showed that combining hyperspectral remote sensing data with machine learning models, such as Random Forests and Support Vector Machines (SVM), can significantly improve yield predictions and agricultural monitoring, even in regions affected by climate change. Jakaria et al. [109], propose a smart weather forecasting system for Tennessee, using historical data from weather stations and simple ML models. The approach provided accurate, resource-efficient weather predictions, particularly beneficial for agriculture where timely forecasts are crucial for effective decision-making. Ayaz et al. [110] discussed IoT-based smart agriculture, emphasizing the role of wireless sensors and UAVs in improving crop monitoring, irrigation, and pest control. The work illustrated how IoT technologies are crucial in enhancing the precision and sustainability of farming practices. Murugan et al. [103] develop an AI-based weather monitoring system integrating IoT devices and deep learning algorithms. The system was designed to predict weather patterns accurately, aiding in agricultural decision-making, particularly for areas vulnerable to unpredictable weather. Sharma et al. [26, 27]

review the application of machine learning in precision agriculture, focusing on the prediction of soil parameters, crop yield, and disease detection. The study underscored how ML models can reduce environmental impact and improve productivity by utilizing IoT and remote sensing data. Jabed et al. [105] review ML and deep learning techniques for crop disease prediction. The work emphasizes the role of CNNs and other advanced models in enhancing disease detection accuracy, ultimately improving crop management and yield. Benos et al. [106] explore various ML models applied to crop management, water, and livestock management. The study highlighted the benefits of machine learning in improving resource use efficiency and sustainability in agriculture. Mohyuddin et al. [107], evaluate the integration of ML in precision farming, focusing on autonomous vehicles, drones, and intelligent irrigation systems. The review pointed out the role of ML in enhancing productivity while reducing resource usage, especially through optimized fertilizer and water application. Wang et al. [108] provides a comprehensive review on integrating remote sensing with machine learning for precision agriculture. The study highlighted the hyperspectral and UAV remote sensing data, combined with machine learning algorithms improve yield predictions and resource management in agriculture, even in the face of climate change challenges. Araujo et al. [111], review the current trends, challenges, and future perspectives in the application of machine learning to agriculture. They highlighted how ML models are being used to address complex agricultural issues, from predicting crop yields to optimizing irrigation schedules, emphasizing the potential of AI to transform agriculture globally. Zaiani et al. [112] focused on global solar radiation prediction using machine learning algorithms and satellite images. The study demonstrated that ML models, when combined with satellite data, could provide highly accurate predictions of solar radiation, an essential factor for optimizing solar energy use in agricultural systems. Tricha and Moussaid [113] evaluates machine learning models for precipitation prediction in Casablanca City. The study compared performance of different machine learning and demonstrated that gradient boosting algorithms significantly improved precipitation forecasts, offering potential for better water management in arid agricultural regions. Emami et al. [114] backtracking search-based extreme gradient boosting algorithm for predicting soil moisture using meteorological variables. The model demonstrated improved accuracy in predicting soil moisture, which is crucial for optimizing irrigation in agriculture, particularly in water-scarce areas. Weyn et al. [80] apply deep learning techniques to weather prediction, specifically for forecasting 500-hPa geopotential height. The study demonstrated that deep learning models outperform traditional weather forecasting methods, particularly in predicting large-scale atmospheric patterns, which are critical for agricultural decision-making. Nuthalapati and Nuthalapati [115], investigated the use of dominant gradient boosting algorithms for accurate weather forecasting. The study shows that hybrid models, combining gradient boosting with deep learning, improved weather prediction accuracy, which can be beneficial for agriculture by providing more reliable forecasts for crop management. Madala et al. [116], examine the effectiveness of hybrid machine learning algorithms in improving weather forecast accuracy by integrating multiple machine learning techniques, the model achieved high accuracy in weather predictions, offering potential applications for agriculture, particularly in areas affected by unpredictable climate patterns. Bhagavathi et al. [117] propose a hybrid C5.0 machine learning algorithm for weather forecasting and prediction. Their model showed strong performance in predicting weather patterns.

Azabadi and Badreldin [118], review the use of remote and proximal sensing technologies combined with machine learning models to predict potato crop yield and manage nitrogen. The study emphasized the role of ML models in improving precision agriculture by providing accurate yield predictions and optimizing nutrient management practices in potato farming. Kumar et al. [119] discussed the use of machine learning techniques in predicting soil organic carbon (SOC) for sustainable agriculture. The research utilized geospatial data alongside machine learning models, such as Random Forest and Support Vector Machines (SVM), to accurately predict SOC levels, thereby improving soil health management practices. Liu and Zhang [120], present a methodology integrating genetic algorithms with machine learning models for crop prediction. The approach helped to optimize the accuracy of yield forecasts by considering environmental factors such as soil quality and climate data, showcasing the potential of genetic algorithms to enhance agricultural decision-making. Zhang et al. [5] compare the performance of various machine learning models in predicting plant growth using IoT data. The research shows that models like Deep Neural Networks (DNN) and XGBoost outperformed traditional methods in predicting plant growth under different environmental conditions, demonstrating the power of IoT data in precision farming. Jin et al. (2023), highlight the significance of feature importance in crop prediction models using machine learning by analyzing the impact of different environmental variables on crop yield, the study emphasized the importance of selecting the right features for training ML models, which can improve the reliability of yield predictions. Ravindran et al. [121] introduce an IoT-based recommender engine for yielding better crops. The model leverages real-time data from IoT sensors to suggest optimal crops based on environmental conditions and soil characteristics, helping farmers increase productivity by making data-driven decisions. Chen et al. propose an IoT-based agriculture trend prediction model based on weather data. The model utilized machine learning algorithms, such as SVM and decision trees, to forecast agricultural trends, including crop yields and disease outbreaks, based on seasonal weather patterns. Rahman et al. [122], present an ML-based yield prediction system for smart agriculture, using IoT data. The system integrated environmental data such as temperature, soil moisture, and rainfall to forecast crop yields with high accuracy, which can help optimize resource allocation and improve farm productivity. Patel and Thakur [123], highlight the role of IoT and AI in building climate change-resilient smart agriculture systems integrating weather forecasts with AI algorithms, they demonstrated how these technologies could enable farmers to adapt to changing climate conditions and mitigate risks associated with extreme weather events. Smith et al. [3] propose an IoT-based dynamic Bayesian prediction system for crop evapotranspiration in soilless cultivations. The system used Bayesian networks, provided accurate predictions of water requirements, which is essential for optimizing irrigation and reducing water wastage in controlled environments. Zhao et al. [124] investigate the prediction of net radiation in naturally ventilated greenhouses, based on external solar radiation data. The model used machine learning algorithms to estimate reference evapotranspiration (ET), offering insights into how greenhouse operations can be optimized to improve crop yields and reduce water consumption. Singh et al. [76] propose a framework to predict mortality risk from synthetic agrochemical exposure, merging exposure duration, chemical types, demographic data, and health outcomes. This shows the multidimension of ML prediction in our daily life. Vijayalakshmi et al. [125], explore machine learning models and spiking neural network's ability in predicting weather patterns and crop yields. The study demonstrated that ML models can be used to optimize agricultural decisions by predicting rainfall, temperature, and other weather parameters that influence crop growth. Zubair et al. [94] examine a deep learning-based agricultural recommendation system, incorporating weather forecasts to recommend optimal crops. The system demonstrates the ability of deep learning models to integrate weather data and suggest the best farming practices, contributing to higher crop yields. Ahmed et al. [96] develop a machine learning approach for predicting crop yield and disease by integrating soil nutrition and weather factors. The system used data from various sources, including weather stations and soil sensors, to provide accurate forecasts for both crop yield and potential disease outbreaks, enhancing decision-making for farmers. Dhungel et al. [126] proposes a biophysical algorithm (BAITSSS) to predict evapotranspiration (ET) by integrating satellite data. The model provided real-time predictions of ET, crucial for irrigation management in agriculture. The research emphasizes the role of weather data in improving water-use efficiency for crop production. Kocian et al. [127] utilize a dynamic Bayesian model for predicting crop evapotranspiration in soilless cultivations. The model incorporated real-time IoT data to provide more accurate evapotranspiration predictions, which is vital for optimizing water usage in hydroponic farming systems. Saadon et al. [128] investigate the prediction of net radiation in greenhouses using machine learning models. The study shows that solar radiation data can be used effectively to estimate reference evapotranspiration (ET), which is vital for managing irrigation and enhancing crop growth in controlled environments. Nawaz et al. [129], illustrate how integrating weather forecasts with AI models can help farmers adapting to changing climate conditions, leading to more sustainable farming practices. Shen et al. [130] revisit Lorenz's early studies on weather predictability, using advanced machine learning techniques to explore two-week predictability limits. The research contributes in understanding weather forecast limitations, which is critical for improving forecasting systems used in agriculture to predict seasonal weather patterns.

Bansal et al. [94] present a study that predicts winter wheat crop yield using multiple heterogeneous datasets and machine learning models. Their comparative analysis demonstrated that integrating diverse datasets with machine learning techniques, such as SVM and Random Forest, provides more reliable predictions for crop yields under varying climatic conditions. Zubair et al. [32] explore the use of deep learning for agricultural recommendations. The approach integrated multivariate weather forecasting with a recommendation system to suggest the best crops to grow based on predicted weather patterns and helping farmers optimize their production. Ahmed et al. (2024) developed a machine learning-based system for crop yield and disease prediction, integrating weather factors and soil nutrition data. The system highlights how combining soil and weather data with machine learning models can improve both yield prediction accuracy and disease management strategies in agriculture.

5 Section III. Research method

In this section the proposed methodology follows four steps as below:

- Formulation of key research question

- Formulation of criteria for the selection of articles
- Evaluation metrics
- Analysis of results

6 Research questions

To come up with a comprehensive analysis for this study, the following research questions were set:

RQ1: Which machine learning and deep learning techniques are suitable for the prediction of meteorological parameters and crop yield.

RQ2: What are meteorological parameters considered with impact to crop yield and productivity.

RQ3: What are contribution and limitation of selected Machine learning and opportunity for future work.

RQ1 explore different machine learning techniques used in the prediction of meteorological parameters such as temperature, rainfall and impact in crop yield. The aim is to give light to the readers and researchers the approach used and proposed solution to the problem highlighted.

RQ2 aims to identify meteorological parameters affecting crop yield and productivity. The information is crucial for model development.

RQ3 aims to identify contribution of deployed machine learning, they limitations and opportunity for improvement.

7 Selection criteria

The process of identifying relevant work was specifically based on the key words such as Meteorological parameters, machine learning techniques, crop yield prediction, artificial intelligence, smart agriculture and crop yield prediction using machine learning. Articles were selected from the following database sources: Google Scholar, Science Direct, IEE Xplore, ResearchGate, Books related to the subject matter.

To select appropriate papers in regard to the area of research; focus was made on journal papers, conference papers and books. Considering the advancement of emerging technologies, selection was made on published research papers between 2018 and 2025. Figure 7 presents Frequency of selected Journals compare to the year of publication.

For proper interpretation and consideration of the content, English language and research papers related to machine learning techniques with application in agriculture were considered in this article. Considering that the study requires proper selection of research works, Fig. 8 provide detail procedure for paper selection.

From the study, 232 papers were selected for review, however, after filtering 24 were found to be dated before 2018 and not reflecting properly the area of research, and found to be lower quality compared to the expectation. Journals considered for review are 158.

8 Evaluation metric

Considering that different machine learning techniques have been used in the prediction of weather parameters and crop yield, it is paramount to use evaluation metric to assess the efficiency and effectiveness of the machine learning models. Key performance metrics have been used in this review of different research papers, evaluation metrics like Mean absolute error, Root mean squared error and coefficient of determination were

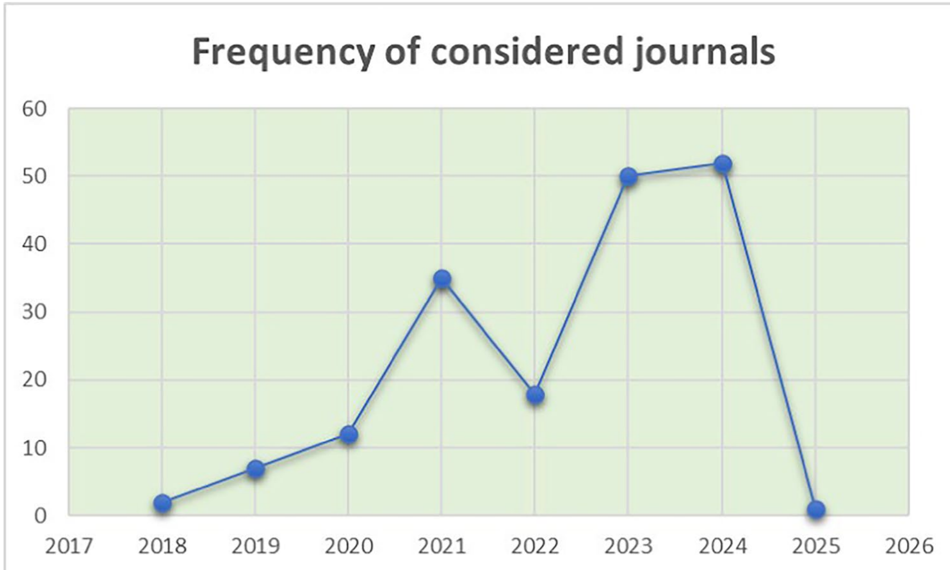

Fig. 7 Distribution of selected journals over publication years

evaluated for decision making. Mean absolute error (MAE) provide difference between predicted and actual value for the regression algorithms. The formula for the mean squared error is

$$\mathrm{MAE} = \frac{1}{\mathrm{n}}\sum_{\mathrm{i}=1}^{\mathrm{n}} |\mathrm{y_i} - \hat{y}_1| \tag{1}$$

where: n is the number of data points; yi is the actual (observed) value for the i-th data point and yî is the predicted value for the i-th data point.

Root Mean Squared error (RMSE) provides the root mean square difference between the anticipated and real value.

$$\mathrm{RMSE} = \sqrt{\frac{1}{\mathrm{n}}\sum_{\mathrm{i}=1}^{\mathrm{n}} (\mathrm{y_i} - \hat{y}_1)^2} \tag{2}$$

where: where: n is the number of data points; yiis the actual (observed) value for the i-th data point and yî is the predicted value for the i-th data point.

Coefficient of determination (R^2): statistical measures that examine the variance in dependent variables in regression models

$$\mathrm{R}^2 = 1 - \frac{\sum (\mathrm{y_i} - \hat{y}_1)^2}{\sum (\mathrm{y_i} - \overline{\mathrm{y}})^2} \tag{3}$$

where yi are the observed values, yî are the predicted values and $\overline{\mathrm{y}}$s the mean of the observed values.

9 Discussion

In this study, main focus was made on supervised and unsupervised machine learning algorithms applications applied in weather forecast with application in agriculture activities. Papers considered were the one published between 2018 and April 2025 as

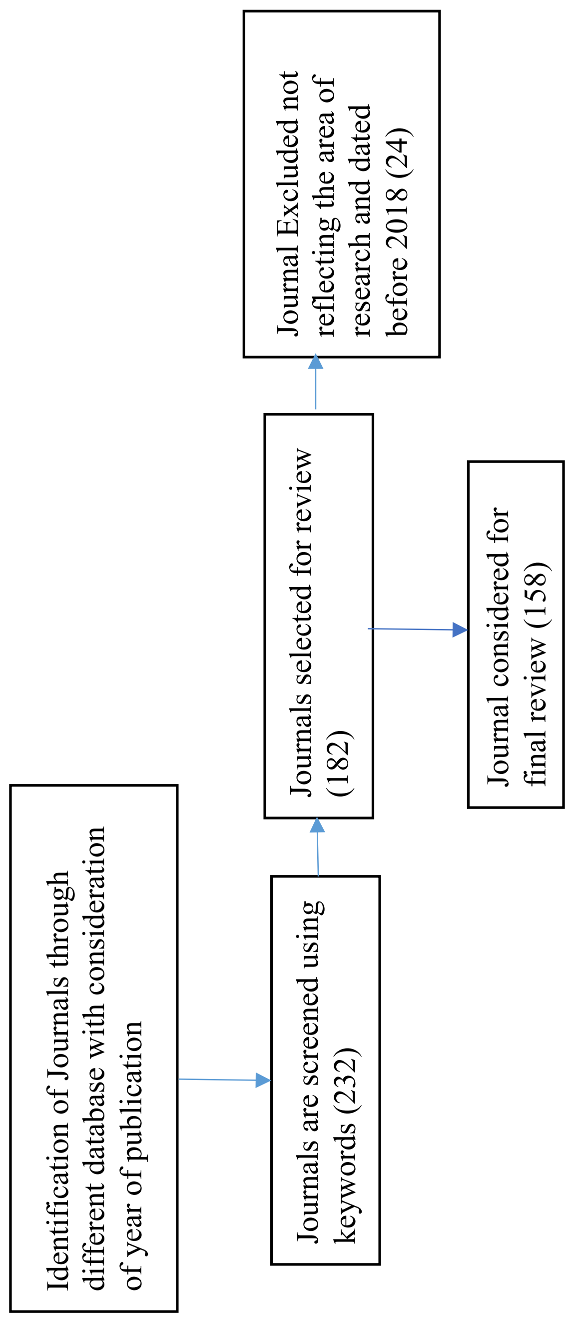

Fig. 8 Methodological framework for literature selection

provided in Fig. 8. Analysis on machine learning performance techniques was key for the future implementation and extension of scope of application. Machine learning techniques considered were Random Forest regression (RF), Deep neural networks (DNN), Hybrid Model, Convolutional Neural network (CNN), Recurrent Neural networks and Support Vector Machine. Figure 9 shows machine learning frequency considered in this study.

10 Choice of Machine learning for crop prediction

RQ1: As per the area of research, article was reviewed and analyze the accuracy of the prediction of machine learning models using meteorological parameters to predict crop yield. In the analysis, hybrid and individual performance in crop yield prediction were considered. Support vector machine, Random Forest Regression and Gradient Boosting machine performance were assessed individually in yield prediction with consideration of soil moisture and drought forecasting. The findings revealed that Gradient Boosting Machine performed with higher accuracy rate for the yield prediction and when combining models, GBM was most accurate in predicting drought forecasting. The support vector machine (SVM), Decision tree (DT), Random Forest and Neural network (NN) were used individual to predict meteorological parameters such as temperature, rainfall, humidity and air pressure; the study revealed that the hybrid models improved prediction accuracy. The combination of convolution neural network and deep learning network performed better than individual performance. The CNN was also compared to other traditional models for wheat yield and found outperformed the traditional model. The use of spatial- temporal attention network improve predictive accuracy for meteorological data. For the prediction of climate variability, the prediction model DF, RF and GBM were also evaluated and found Random Forest to be more accurate compare to other models. In the prediction of temperature parameters Artificial neural networks, Support Vector Machine and decision trees were analyzed individually were used and found that the fusion model outperformed individual model. Following comparison analysis conducted support vector machine, Convolutional neural networks, Random forest and Gradient Boosting Machines are mostly used in the prediction on meteorological parameters and crop yield production; however, the combination of models in hybrid models such as CNN-DNN-RNN, SVM-DT-RF-NN, SVM-RF-GBM increases the accuracy in the prediction on both meteorological parameters and crop yield.

11 Meteorological Parameters considered in crop yield prediction

RQ2: Meteorology data parameters impacting crop yield prediction such as temperature, humidity, rainfall, sun radiation plays a key role in agriculture prediction where quality and quantity of production depends. In this paper frequency of meteorological used in the prediction using different machine learning techniques is provided in Fig. 10.

Following results estimation on coefficient of determination (R^2) for different ML techniques including support vector machine, Random Forest, decision model, convolution neural network, Gradient Boosting machine, Neural network are relatively closer to 1; this imply that the meteorological parameters considered in Fig. 10 are prominent and should be considered in the prediction models, however, the hybrid combination of deep learning models show high performance compared to individual models.

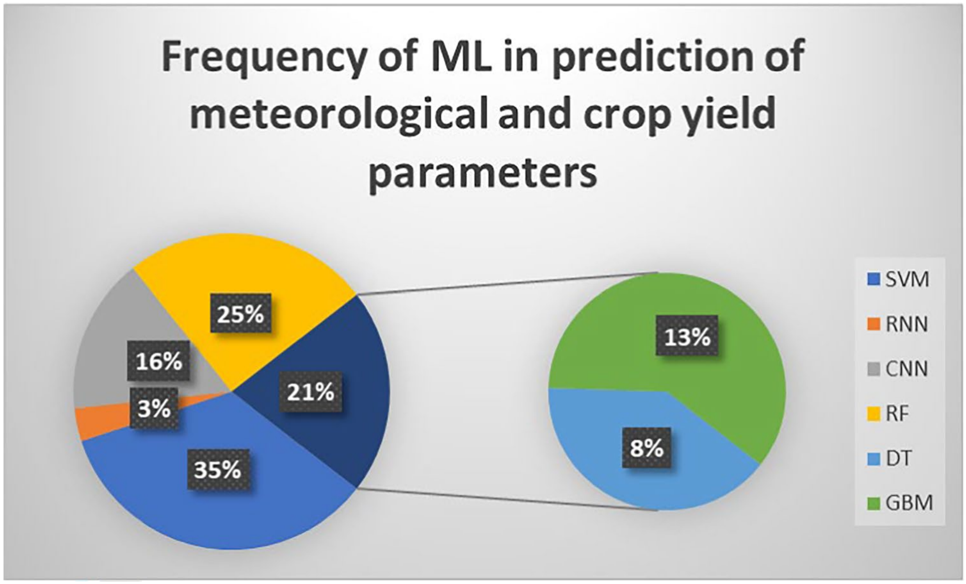

Fig. 9 Frequency of machine learning models applied in this study

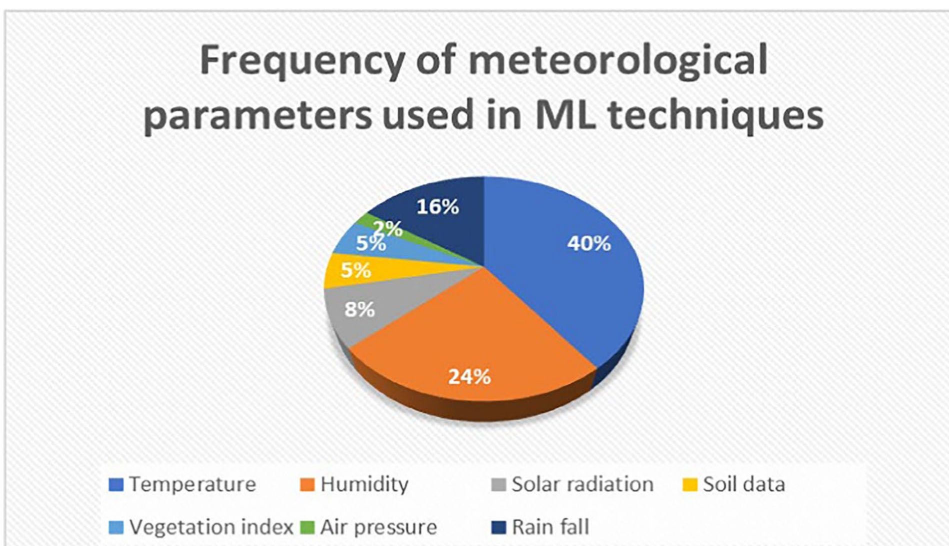

Fig. 10 Meteorological parameters forecasted using machine learning models

12 Conclusion

The study depicted contribution of different machine learning models used in the prediction of crop yield using meteorological parameters. The study focused on ensemble model and deep machine learning techniques used in the prediction of crop yield. Different study highlights the contribution of machine learning in predicting precipitation, temperature, crop yield. Random Forest shows high accuracy in predicting crop yield with R^2 of 0.875 for Irish potatoes and 0.817 for maize. For the prediction of cotton Extreme gradient boost had limited error of 0.07, Ensemble models (XGBoost, RF) outperformed other methods with R^2 of 0.99. Qualitative and quantitative results a combination of convolution neural networks, artificial neural networks with other models shows higher performance.

For the future perspective deep learning models will be proposed in the prediction of meteorological parameters in consideration of crop yield production for the maize crop in Kayonza district, Rwanda. A dataset on temperature, rainfall, humidity and soil acidity will be considered in the study.

Limitation: In this research, focused was on journals referenced in the area of study; however, only limited number of journals were reviewed; additional to that analysis tools used in this study are not exhaustive, however, the researcher made all effort to provide answer to the research questions.

13 Authors 'contributions

Bobo Mafrebo Lionel is the corresponding author and was involved in Conceptualization of the work, Richard Musabe performed the review of proposed model, Omar Gatera validate all concepts unitized, Twizere Celesin review the final manuscript.

Abbreviations

RCN	Recurrent Neural Networks
DNN	Deep Neural Network
CNN	Convolution Neural Networks
RF	Random Forest
DT	Decision tree
GBM	Gradient Boosting Machine
ANN	Artificial Neural Networks
ML	Machine learning
SVM	Support Vector Machine
ELM	Ensemble Learning Models
RMSE	Root mean squared Error
MAPE	Mean absolute percentage error
KNN	K-nearest Neighbors

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Author contributions
A. BOBO MAFREBO Lionel, Play a key role in the conceptualization in regard to the area of research and future development of prototype. B. Richard Musabe, Play key role in the review of the proposed model C. Omar Gatera, review and validate the concept used D. Twizere Celestin, Review the final manuscript

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Data availability
No datasets were generated or analysed during the current study.

Declarations

Ethical approval and consent to participate
The authors affirm that there is no conflict of interest, financial that could have influenced the outcomes of this study. All source of literatures has been appropriately acknowledged, and the work adheres to principles of academic integrity, transparency, and responsible research conduct.

Clinical trial number
Not applicable.

Consent to publication
Not applicable.

Conflict of Interest
The authors declare no competing interests.

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