REF NO	AUTHORS	TECHNIQUES USED	ADVANTAGES	LIMITATIONS
1.	Leelavathi Kandasamy Subramaniam, Rajasenathipathi Marimuthu	Deep Learning (DL), Dimensionality Reduction (DR) using Squared Exponential Kernel-based Principal Component Analysis (SEKPCA), Weight-Tuned Deep Convolutional Neural Network (WTDCNN) for classification	Achieves an improved accuracy of 98.96% in crop yield prediction, Tailored specifically for predicting yields of Indian regional crops, Demonstrates superior performance compared to existing methods	Requires significant computational resources for deep learning and dimensionality reduction techniques, Highly dependent on the quality and completeness of the dataset, Highly dependent on the quality and completeness of the dataset
2	Thomas van Klompenburga, Ayalew Kassahuna, Cagatay Catalb	Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), Long-Short Term Memory (LSTM), Deep Neural Networks (DNN)	Provides a comprehensive review of machine learning algorithms and features used in crop yield prediction, Identifies ANN as the most applied machine learning algorithm and CNN as the most widely used deep learning algorithm, Offers suggestions for further research based on the analysis of 50 machine learning-based and 30 deep learning-based studies	The review may be limited by the inclusion and exclusion criteria applied, potentially missing relevant studies, Focuses primarily on temperature, rainfall, and soil type as features, which might overlook other important factors, The synthesis of diverse studies might lead to generalizations that do not apply to specific crops or regions
3	Anna Chlingaryana, Salah Sukkarieha, Brett Whelan	Machine learning methods, Remote sensing (RS) systems, Fusion of different sensor modalities, Hybrid systems, Integration of expert knowledge	Improved yield production and nitrogen management, Reduced operating costs and environmental impact,	Requirement of processing enormous amounts of remotely sensed data, Challenges in integrating and fusing different sensor modalities,

			Capability to process large amounts of data and handle complex tasks, Cost-effective and comprehensive solutions for crop and environment state estimation. Enhanced decision-making in precision agriculture	Need for further development of hybrid systems and ML techniques, Dependency on advanced sensing technologies and expert knowledge, Potential for high initial setup and maintenance costs for RS and ML systems
4	Ekaansh Khosla, Ramesh Dharavath, Rashmi Priya	Modular Artificial Neural Networks (MANNs), Support Vector Regression (SVR)	Effective in predicting monsoon rainfall and crop yield, Helps in making proper agricultural strategies to increase crop yield, Outperforms other machine learning algorithms in predicting kharif crop production	Relies heavily on accurate rainfall data for prediction, May not account for all climatic and soil variables influencing crop yield, Specific to the region of Visakhapatnam, might require adjustments for other regions
5	P.S. Maya Gopal, R. Bhargavi	Hybrid MLR-ANN model, Feed Forward Artificial Neural Network with Back Propagation, Comparison with ANN, MLR, SVR, KNN, RF models	Improved prediction accuracy, Efficient initialization of ANN’s input layer weights and bias, Reduced computational time	Requires extensive data and computational resources, Complexity in model implementation and comparison
6	Xubo Zhang, Minggang Xu, Nan Sun, Wei Xiong, Shaomin Huang, Lianhai Wu	SPACSYS model for simulation, Long-term experimental data	Enhanced crop yield and soil fertility, Increased soil organic carbon (SOC) and nitrogen stocks	Higher soil respiration and nitrogen losses with mineral fertilizers plus manure, Environmental risks associated with increased carbon emissions

7	X.E. Pantazi, D. Moshou, Alexandridis, R.L. Whetton, A.M. Mouazen	On-line proximal soil sensing, Satellite imagery for crop growth characteristics, Supervised self-organizing maps (SKN, CP-ANN, XY-F)	High-resolution data collection, Reduced labour and time costs, Accurate yield prediction with SKN model	Complexity in handling data from various sensors, Need for cross-validation to ensure prediction accuracy
8	G. Prabakaran, D.Vaithiyanathan, Madhavi Ganesanc	Fuzzy logic systems, MATLAB for feasibility rules analysis	Reduction in fertilizer consumption, Improved crop productivity, Tailored fertilizer recommendations based on land report and expert knowledge	Requires extensive field measurements and lab analysis, Dependence on multi-domain experts for rule formation
9	Xinpeng Xu, Ping He, Fuqiang Yang, Jinchuan Ma, Mirasol F.Pampolino, Adrian M.Johnston, Wei Zhoub	Yield response analysis, Agronomic efficiency (AE) evaluation, Relative yield measurement, Soil indigenous nutrient supply assessment, Nutrient Expert (NE) decision support system	Increased nutrient use efficiency, Improved yield and profits, Enhanced agronomic efficiency, Reliable fertilizer recommendations	Dependency on extensive data collection, Continuous optimization needed, Complex relationship analysis
10	Abdelraouf M. Ali, Mohamed Abouelghar, A.A. Belal, Nasser Saleh, Mona Yones, Adel I. Selim, Mohamed E.S. Amin, Amany Elwesemy, Dmitry E. Kucher, Schubert Maginan, Igor Savin	Multispectral and hyper spectral data analysis, Radar and LiDAR imagery	High spatial resolution for accurate crop monitoring, Ability to identify and quantify crop biochemical and biophysical parameters, Early detection of plant infections	Field or laboratory devices are inefficient for large-area monitoring, Challenges in applying techniques uniformly under different agricultural conditions

11	Tamil Selvi M, Jaison B	Deep Belief Network for feature learning and pre-training, Decision Tree & K-Means Clustering (HDTKM) with Particle Swarm Optimization (PSO) for training, Naive Bayes Clustering with PSO for testing	High prediction accuracy (98.35%), Low error rate (0.0314), Assists farmers in selecting the optimal crop for maximum yield	Requires extensive computational resources for deep learning and clustering algorithms, Complexity in implementing and fine-tuning multiple machine learning models
12	Bin Peng Kaiyu Guan Wang Zhou Chongya Jiang Christian Frankenberg Ying Sun Liyin He Philipp Köhler	Satellite-Based Data: Solar-Induced Chlorophyll Fluorescence (SIF) from OCO-2, TROPOMI, and GOME-2 Vegetation Indices (NDVI, EVI, NIRv) Land Surface Temperature (LST) Machine Learning Algorithms	1.Comparative Analysis: The study benchmarks the performance of SIF against other remote sensing variables like NDVI, EVI, NIRv, and LST, providing a comprehensive analysis of their relative effectiveness. 2.Potential for Future Improvements: With the accumulation of more high-resolution and good-quality SIF products, the predictive performance can be expected to improve further.	1.Inconsistent Performance: High-resolution SIF products did not consistently outperform other satellite-based remote sensing variables in all evaluated cases. 2.Dependence on Crop Types and Data: The relative performance of different remote sensing variables in yield prediction varies with crop types, testing methods, and the length of training data records.
13	Khanal, S., Fulton, J., Klopfenstein, A., Douridas, N., Shearer, S. (2018) Kokaly, R.F., Asner, G.P., Ollinger, S.V., Martin, M.E.,	Radiometric Calibration: Adjusting satellite imagery to correct for sensor and atmospheric distortions. Pan-Sharpening: Merging high-resolution	1.High Spatial Resolution: Satellite data (WV and PS) can provide reliable estimates of field-scale yield, improving real-time and efficient agricultural	1.Vanishing Gradient Problem: Deep networks can suffer from the vanishing gradient problem, where gradients become too small for effective backpropagation in

		panchromatic images with lower-resolution multispectral images to enhance spatial resolution.	management (satellite data and deep…). 2.Robust Feature Extraction: Utilization of spectral and textural indices enhances the prediction accuracy. 3.Deep Learning: Application of deep learning architectures like ResNet-18 allows for better handling of large and complex datasets (satellite data and deep…).	very deep networks (satellite data and deep…). 2.Data Requirement: High-resolution satellite imagery and UAV data collection are resource-intensive and may not always be feasible. 3.Computational Complexity: Implementing and tuning deep learning models require substantial computational resources and expertise(satellite data and deep…
14	Khanal, S., Fulton, J., Klopfenstein, A., Douridas, N., Shearer, S. Kokaly, R.F., Asner, G.P., Ollinger, S.V., Martin, M.E., Wessman, C.A. Kokaly, R.F., Clark, R.N. Kowalik, W., Dabrowska-Zielinska, K., Meroni, M., Raczka, T.U., de Wit, A. Krizhevsky, A., Sutskever, I., Hinton, G.E. Kumar, L., Schmidt, K., Dury, S., Skidmore, A. Kuwata, K., Shibasaki, R.	Deep Neural Networks (DNN) Uses hidden layers and activation functions such as ReLU (Rectified Linear Unit) with dropout and batch-normalization techniques(satellite data and deep…). Convolutional Neural Networks (CNN) Includes architectures like AlexNet, VGG-Net, GoogleNet, and ResNet-18, which are designed to handle image data through multiple convolutional layers to extract features and improve prediction	1.Deep Neural Networks (DNN) Provides robust representation for complex data like crop yield predictions due to its deep learning capability, reducing errors significantly compared to traditional methods (CNN). 2.Techniques like dropout and batch normalization help in reducing overfitting and improving the model's generalization (satellite data and deep…). 3.Convolutional Neural Networks (CNN)	1.Deep Neural Networks (DNN) Requires significant computational resources and large datasets for training to achieve optimal performance (satellite data and deep…). 2.Complexity in tuning parameters such as batch size, learning rate, and dropout rate can be challenging and time-consuming (satellite data and deep…). 3.Convolutional Neural Networks (CNN) Very deep networks can still suffer from training difficulties

		accuracy(satellite data and deep…). Machine Learning Algorithms Decision Trees (DT), Random Forest (RF), Support Vector Machines (SVM), and Long Short-Term Memory (LSTM) networks are used for comparisons and crop yield predictions(CNN).	Deep networks like ResNet solve the vanishing gradient problem, enabling the training of very deep networks for better performance (satellite data and deep…). 4.Superior in handling image data due to its hierarchical structure which captures spatial hierarchies in images effectively (satellite data and deep…).	despite solutions like ResNet, and may require extensive hyperparameter tuning(satellite data and deep…). 4.High computational demand and the need for large labeled datasets for effective training (satellite data and deep…).
15	Christine Musanase, Anthony Vodacek, Damien Hanyurwimfura, Alfred Uwitonze, Innocent Kabandana	Neural Network model for crop recommendations, Rule-based fertilization recommendation system, Machine Learning (ML) and Internet of Things (IoT) for precision farming	High prediction accuracy of 97%, Optimizes agricultural practices and resource use, Provides personalized recommendations for crop and fertilizer based on key growth parameters	Dependency on pre-compiled tables for fertilizer recommendations, May require continuous updates and maintenance of the rule-based system for evolving agricultural conditions
16	Haoru Li, Xurong Mei, Jiandong Wang, Feng Huang, Weiping Hao, Baoguo Li	Drip fertigation for synchronized water and nitrogen supply, Meta-analysis to evaluate the effects of drip fertigation on yield, water productivity (WP), and nitrogen use efficiency (NUE), Comparison with traditional irrigation (furrow or flood) and fertilization	Significant increase in crop yields (12%), WP (26.4%), and NUE (34.3%), Reduction in crop evapotranspiration (ET) by 11.3%, Potential for irrigation water saving (WSP) and nitrogen saving (NSP) without reducing crop yields, Highest improvements	Effectiveness varies depending on crop types, edaphic, climatic, and managerial factors, Requires precise management and monitoring to achieve the reported benefits, Potentially higher initial setup costs compared to traditional methods

		(broadcasting nitrogen fertilizer)	observed in potato yield (40.3%) and WP (100.3%), and fruit NUE (68.2%), Best performance in semiarid regions	
17	Li Tian, Chun Wang, Hailiang Li, Haitian Sun	Ecological distance algorithm for yield prediction, Integration of weather, soil, and behavioural parameters, Pearson correlation coefficient and total sensitivity index for parameter selection, Data assimilation technique to refine crop yield predictors	Higher prediction accuracy compared to original models, Incorporates multiple impact parameters for comprehensive yield prediction, Improved model output closer to actual sample results	Complexity in combining multiple parameters and algorithms, Requires detailed and accurate data collection for effective predictions, May need significant computational resources for data assimilation and model training
18	Jairos Rurinda, Shamie Zingore, Jibrin M. Jibrin, Tesfaye Balemi, Kenneth Masuki, Jens A. Andersson, Mirasol F. Pampolino, Ibrahim Mohammed, James Mutegi, Alpha Y. Kamara, Bernard Vanlauwe, Peter Q. Craufur	Nutrient Expert (NE) computer-based decision support system, Calibration of NE using data from on-farm nutrient omission trials, Performance trials to evaluate NE recommendations relative to soil-test based and blanket fertilizer recommendations	Generates site-specific fertilizer recommendations based on yield response and nutrient use efficiency, Maintains high maize yields while reducing fertilizer input costs, Provides an effective alternative to soil testing, beneficial for smallholder farmers, Improves agronomic use efficiencies of nutrients (N, P, K)	Variability in maize yield response to fertilizer across different geographic locations, Secondary and micronutrient benefits are area-specific, limiting generalizability, Initial setup and calibration of NE may require extensive field trials and data collection
19	1.Kavita Jhajharia 2.Pratistha Mathur 3.Sanchit Jain	Random Forest (RF) Support Vector Machine (SVM)	High Accuracy: Machine learning and deep learning models, particularly deep	Data Dependency: The accuracy of the models is highly dependent on the quality and

	4.Sukriti Nijhawan	Artificial Neural Networks (ANN) Convolutional Neural Networks (CNN) Long Short-Term Memory (LSTM)	learning models, can provide high accuracy in predictions due to their ability to capture complex patterns in the data. Automation: These techniques allow for automated processing and analysis, reducing the need for manual intervention. Scalability: Models can be scaled to handle large datasets, making them suitable for extensive agricultural datasets.	quantity of the data available. Insufficient or poor-quality data can lead to inaccurate predictions. Complexity: Deep learning models, in particular, can be complex and require significant computational resources and expertise to implement and maintain. Overfitting: There is a risk of overfitting, where models perform well on training data but poorly on unseen data, reducing their generalizability.
20	Yan Li Kaiyu Guan Albert Yu Bin Peng Lei Zhao Bo Li Jian Peng	Climate Variables: Vapor Pressure Deficit (VPD) Air Temperature Precipitation Satellite Variables: Enhanced Vegetation Index (EVI) Land Surface Temperature (LST) Modeling Techniques: Linear, Polynomial, and Spline fitting functions	High Predictive Performance: The study achieves high prediction accuracy with a median R^2 of 0.85 and RMSE of 0.90 t/ha (14.3 bu/acre) when using both climate and satellite variables. Improved Predictive Capability: Incorporating satellite data (EVI and LST) significantly improves the model's performance. .	Data Dependency: The accuracy of the statistical model depends heavily on the availability and quality of historical data. Regional and Interannual Variations: The model's performance varies significantly across different states and years, influenced by spatial yield variability and climate conditions.