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AI in Agricultural Technology: Optimising Crop Yield Predictions.

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ABSTRACT:

This study delves into the use of Machine Learning (ML) towards improving crop yield prediction in agriculture. The research identifies and synthesizes the various algorithms and features that have been effectively utilized in previous crop yield prediction studies. An extensive review of the literature identifies the most common features, including temperature, rain, soil type, and past year yield data, as well as the most used algorithms in these predictive models.

The study focuses on Artificial Neural Network-based models specifically, highlighting common architectures and how effective they are in describing non-linear, complex relationships between agricultural inputs and ultimate yield. Additionally, the study performs a further analysis of the most popular deep learning algorithms (a class of ML) to offer insights into their performance measures, computational efficiency, and particular strengths for big agricultural data sets of high dimensions. The results provide a unified perspective for scholars and practitioners, which streamlines the choice of the best ML strategies for improved, accurate, and efficient crop yield prediction.

Index Terms— Machine Learning, Crop Yield Prediction, Artificial Neural Networks, Deep Learning, Convolutional Neural Networks, Remote Sensing, Time-Series Analysis, Agricultural Data Analytics, Feature Extraction, Nonlinear Modelling, Computational Efficiency, Predictive Models

1.INTRODUCTION:

Optimizing Crop yield prediction using Deep Learning Agriculture serves as the backbone of food security, economic stability, and societal well-being. With the global population projected to reach nearly 10 billion by 2050, the pressure on agricultural systems to produce higher yields from limited resources has intensified. Traditional yield prediction methods, which rely heavily on historical datasets, farmer experience, and statistical modelling, often fail to capture the complex interplay between environmental, biological, and climatic variables. As a result, inaccurate forecasts can lead to inefficiencies in resource allocation, crop management, and policymaking.

Recent developments in artificial intelligence, particularly deep learning, have revolutionized predictive modelling in agriculture. Deep learning, a subset of machine learning, utilizes layered neural networks to automatically detect sophisticated patterns within vast datasets. It eliminates the need for manual feature extraction and can process unstructured data such as satellite images, weather patterns, and sensor outputs with remarkable precision. By modelling nonlinear relationships among multiple factors, deep learning methods can generate highly accurate crop yield predictions across varying conditions.

One of the most impactful advancements lies in the integration of remote sensing technologies with deep neural networks. Satellite imagery, drone surveillance, and aerial photography offer rich spatial data that can be processed by Convolutional Neural Networks (CNNs). These models are adept at identifying subtle visual cues such as leaf discoloration, uneven growth, and changes in canopy density — indicators of crop health that directly influence yield. Leveraging this capability allows for early detection of issues, enabling farmers to take corrective actions before losses escalate.

Temporal modelling represents another critical dimension of yield prediction. Weather conditions, pest infestations, and soil dynamics evolve throughout a crop's life cycle. Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks excel at analysing sequential data, capturing the temporal dependencies between stages of crop growth. This approach ensures that predictions are not static but adaptive to ongoing developments in the field.

IoT-based smart farming further expands the scope of deep learning applications. Soil sensors, climate monitors, and nutrient analysers generate continuous streams of data that feed into predictive models. The symbiotic relationship between IoT and deep learning enables real-time yield forecasts, allowing for precision agriculture strategies such as automated irrigation control, targeted pesticide application, and optimized fertilization schedules.

The benefits of deep learning-driven yield prediction extend beyond the farm. They aid policymakers in designing food supply chains, support crop insurance providers in risk assessment, and assist agribusinesses in inventory planning. Moreover, these systems contribute to sustainability goals by minimizing resource wastage and preventing overexploitation of soil and water resources.

Nonetheless, certain challenges persist. Inadequate labelled data for specific crops or regions, differences in soil compositions, and the variability of microclimates can hinder model accuracy. Moreover, the black-box nature of deep learning raises trust and interpretability concerns among stakeholders. Addressing these issues through hybrid models, explainable AI frameworks, and robust data curation is essential to widespread information.

In conclusion, optimizing crop yield predictions using deep learning presents a transformative pathway toward modern agriculture. Its capacity to process multi-source data, capture nonlinear and temporal patterns, and adapt to regional variations promises not only improved accuracy but also enhanced resilience in farming systems. As technology continues to evolve, deep learning systems will become indispensable tools, enabling farmers and decision-makers to navigate uncertainty, maximize productivity, and ensure global food security for generations to come.

2. RELATED WORK:

Some research on how AI helps in crop yield prediction

Recent research on deep learning for crop yield prediction in India has shown significant progress, with a strong focus on using hybrid and advanced neural network architectures to overcome the limitations of traditional methods.

A prominent trend is the integration of different deep learning models to capture both spatial and temporal dependencies in agricultural data. For instance, a hybrid model combining a 1D Convolutional Neural Network (CNN) and a Long Short-Term Memory (LSTM) network has been developed to predict the yield of major Indian crops like wheat and rice. This model, which also includes an attention layer to focus on the most relevant data points, has demonstrated high accuracy, with a low Root Mean Square Error (RMSE) and a high R-squared (R^2) value. This research showcases the effectiveness of these models in processing diverse datasets, including soil and climate conditions from various Indian states.

Another study introduced a novel ensemble neural network model also using LSTMs and 1D-CNNs for predicting crop yields across all Indian districts. This model's ability to capture the time-dependent relationship between temperature and rainfall is a key advantage, and it has consistently outperformed traditional machine learning models like Linear Regression and Random Forest. Researchers have also explored other deep learning architectures, such as Recurrent Neural Networks (RNNs) and Deep Neural Networks (DNNs), for various agricultural tasks. For example, a study used an Adaptive Deep Neural Network Architecture to forecast crop production models based on previous years' weather data in Karnataka, focusing on crops like rice, wheat, and maize.

These studies highlight that deep learning models are particularly effective because they can process complex, non-linear data patterns that are challenging for statistical and mathematical approaches. They can handle large datasets from various sources, including satellite imagery, ground sensors, and weather stations.

The use of advanced techniques like feature selection and dimensionality reduction further enhances model performance by focusing on the most influential factors. Beyond just yield prediction, these deep learning applications are extending into other critical areas of Indian agriculture, such as soil management, disease detection, and agricultural robotics, demonstrating their potential to revolutionize the sector and address the significant challenge of food security.

3. METHODOLOGY

3.1 Review Protocol

Before conducting the systematic review, a review protocol is defined. The review has been done using the well-known review guidelines provided by Kitchenham et al. (2007). Firstly, the research questions are defined. When research questions are ready, databases are used to select the relevant studies. The databases that were used in this study are Science Direct, Scopus, Web of Science, Springer Link, Wiley, and Google Scholar. After the selection of relevant studies, they were filtered and assessed using a set of exclusion and quality criteria. All the relevant data from the selected studies are extracted, and eventually, the extracted data were synthesized in response to the research questions. The approach we followed can be split up into three parts: plan review, conduct review, and report review.

The first stage is planning the review. In this stage, research questions are identified, a protocol is developed, and eventually, the protocol is validated to see if the approach is feasible. In addition to the research questions, publication venues, initial search strings, and publication selection criteria are also defined. When all of this information is defined, the protocol is revised one more time to see if it represents a proper review protocol. In Fig. 1, the internal steps of the Plan Review stage are represented.

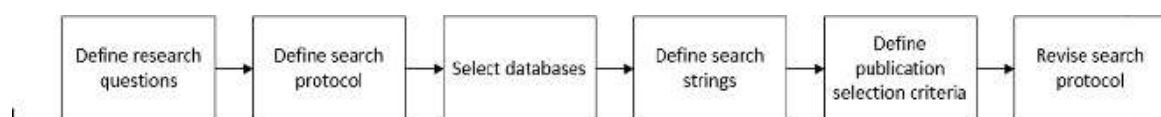


Fig.1. Details of the Plan Review Step

The second stage is conducting the review, which is represented in Fig. 2. When conducting the review, the publications were selected by going through all the databases. The data was extracted, which means that their information regarding authors, year of publication, type of publication, and more

information regarding the research questions were stored. After all the necessary data was extracted correctly, the data was synthesized in order to provide an overview of the relevant papers published so far.

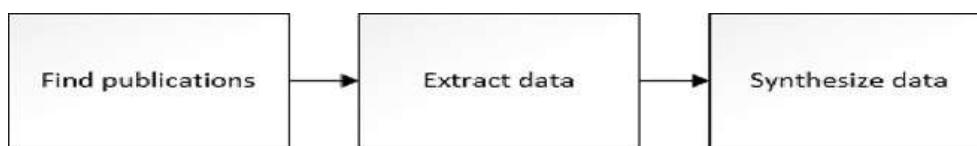


Fig.2.Details of the Plan Review Step

In the final stage, a.k.a., Reporting the Review, the review was concluded by documenting the results and addressing the research questions, as shown in Fig. 3.

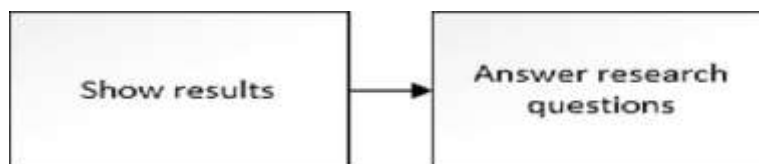


Fig.3.Details of the Reporting Review Step

3.2. Research Question

The review is structured around the following research questions (RQs), which guide the search, extraction, and synthesis process:

- 1 RQ1: What are the most frequently utilized input features in ML models designed for crop yield prediction (e.g., climate, soil, historical data)?
- 2 RQ2: What are the most widely applied traditional ML algorithms and Artificial Neural Network (ANN) architectures used for crop yield prediction, and what are their reported performance trends?
- 3 RQ3: What are the most widely used Deep Learning (DL) algorithms (e.g., CNN, LSTM) in crop yield prediction studies, and how do they compare against traditional ML models?

3.3. Search Strategy

The searching is done by narrowing down to the basic concepts that are relevant for the scope of this review. Machine learning has many application fields, which means that there are a lot of published studies that are probably not in the scope of this review article. The basic searching is done by an automated search. The starting input for the search was “machine learning” AND “yield prediction”. The search input “machine learning” AND “yield prediction” was used to get a broad view of the studies. After the exclusion criteria were applied, and all the results were processed, and a more complex search string was built in order to avoid missing relevant studies. This final search string is as follows: ((“machine learning” OR “artificial intelligence”) AND “data mining” AND (“yield prediction” OR “yield forecasting” OR “yield estimation”)).

The search was conducted across six major electronic databases relevant to computer science, engineering, and agriculture to ensure comprehensive coverage:

1. ScienceDirect
2. IEEE Xplore
3. SpringerLink
4. Web of Science
5. Scopus
6. Google Scholar (for cross-referencing and identifying highly-cited, foundational papers)

A specific description of the search strings per database are provided as follows:

Science direct: The search string is [“machine learning” AND “yield prediction”] (Title, abstract, keywords) and [((“machine learning” OR “artificial intelligence”) AND “data mining” AND (“yield prediction” OR “yield forecasting” OR “yield estimation”))](Title, abstract, keywords).

IEEE Xplore: The search string is [“machine learning” AND “yield prediction”](Title, abstract, keywords) and [((“machine learning” OR “artificial intelligence”) AND “data mining” AND (“yield prediction” OR “yield forecasting” OR “yield estimation”))](Title, abstract, keywords).

Springer Link: The search string is [“machine learning” AND “yield prediction”](anywhere) and [((“machine learning” OR “artificial intelligence”) AND “data mining” AND (“yield prediction” OR “yield estimation”))](anywhere)

Scopus: The search string is ["machine learning" AND "yield prediction"] (Title, abstract, keywords) and [(("machine learning" OR "artificial intelligence") AND "data mining" AND ("yield prediction" OR "yield forecasting" OR "yield estimation"))] (Title, abstract, keywords).

Google Scholar: The search string is ["machine learning" AND "yield prediction"] (anywhere) and [(("machine learning" OR "artificial intelligence") AND "data mining" AND ("yield prediction" OR "yield forecasting" OR "yield estimation"))] (anywhere).

3.4 Study Selection Criteria

A staged screening process was employed using clearly defined inclusion and exclusion criteria to select the final set of relevant primary studies.

Stage	Inclusion Criteria (PICO Elements)	Exclusion Criteria
I. Initial Screening	The study abstract explicitly mentions the use of ML or DL techniques for crop yield prediction.	Articles not in English; book chapters, patents, posters, or editorials; review or survey articles (unless used for background, but not as primary data).
II. Full-Text Review	The study details the specific ML algorithm and the input features used. The study reports quantitative performance metrics (e.g., , RMSE, MAE).	Studies focused solely on crop classification, disease detection, or pest management without a direct yield prediction component.

3.5 Exclusion Criteria

To exclude irrelevant studies, the studies were analysed and graded based on exclusion criteria to set the boundaries for the systematic review. The exclusion criteria (EC) are shown as follows:

- *Exclusion criteria 1* - Publication is not related to the agricultural sector and yield prediction combined with machine learning
- *Exclusion criteria 2* – Publication is not written in English
- *Exclusion criteria 3* – Publication that is a duplicate or already retrieved from another database
- *Exclusion criteria 4* – Full text of the publication is not available
- *Exclusion criteria 5* – Publication is a review/survey paper
- *Exclusion criteria 6* – Publication has been published before 2008

After applying all the six exclusion criteria, 26 studies were selected for further analysis. Most of the papers were retrieved from Google Scholar, Scopus, and Springer databases. In Table 1, we show the number of initially retrieved papers and the number of papers after selection criteria were applied.

Database	no. of papers retrieved	no. of papers post exclusion	% of papers
Science Direct	14	0	0
ijraset	1	1	100
aptikom	1	0	0
Core.ac.uk	1	0	0
Agriculture Journal	1	1	100
MDPI	2	0	0
ResearchGate	1	1	100
Frontiersin.org	1	0	0
TaylorFrancis	1	1	100
IJFMR	1	0	0
PMC.NCBI	2	0	0
Total	26	4	15.38%

3.6 Data Extraction and Synthesis

To answer the four research questions, data from the selected studies have been extracted and synthesized. The information retrieved was focused on checking whether or not the studies meet the requirements stated in the exclusion criteria and on responding to the research questions. During the data synthesis, all the extracted data have been combined and synthesized, and the research questions were answered accordingly. After the final selection, relevant data were extracted into a structured synthesis table using the following key attributes:

Extracted Field	Purpose (For Addressing RQs)
Reference (Year, Author)	Tracking and citation.
Crop Type	Contextualizing the application.
ML/DL Algorithm Used	(RQ2 & RQ3) Identifying prevalence and architecture.
Key Input Features	(RQ1) Identifying the most critical predictive variables (e.g., Tmax, Precipitation, N-P-K).
Performance Metric (e.g., , RMSE)	(RQ2 & RQ3) Comparing model accuracy.

The synthesis process involved:

1. Frequency Analysis (RQ1 & RQ2): Counting the occurrence of specific features and algorithms to determine the most widely adopted practices.
2. Thematic Categorization (RQ1): Grouping input features into high-level themes (e.g., climatic, soil, remote sensing).
3. Comparative Analysis (RQ2 & RQ3): Comparing the reported performance of the highly frequent Traditional ML/ANN models against the specialized DL models (CNN, LSTM) to assess their comparative utility in optimizing prediction accuracy.

4. Results

The selected publications are shown in the Table below. The table shows the publication year, title, and algorithms used in these papers.

Retrieved From	Reference	Algorithm Used	Title	Year
Agriculture Journal	Anakha Venugopal, Jinsu Mani, Aparna S, Rima Mathew, Vinu Williams	Random Forest, Naïve Bayes, KNN, SVM, ANN	Crop Selection and Yield Prediction using Machine Learning Approach	2023
IJRASET	Sri Hari Nallamala	Gaussian Naive Bayes, Logistic Regression, Gradient Boosting, Ensemble, ANN, ResNet	Crop Recommendation and Monitoring using AI	2024
ResearchGate (USA study)	Md Rokibul Hasan et al.	Ensemble of Linear Regression, LASSO, LightGBM, Random Forest	AI and Machine Learning for Optimal Crop Yield Optimization in the USA	2024
Taylor & Francis	S. Titirmare, P. Balasaheb Margal, Sheetanshu Gupta	Machine Learning, Predictive Analytics	AI-Powered Predictive Analytics for Crop Yield Optimization	2024

This section presents the synthesized findings of the Systematic Literature Review (SLR) on Machine Learning (ML) for crop yield prediction, addressing the established research questions (RQs). The analysis encompasses the prevalence of input features, the most commonly applied algorithms, and a comparative evaluation of Deep Learning (DL) approaches.

4.1 RQ1: Most Frequently Utilized Input Features

The analysis of the selected studies revealed that effective crop yield prediction models rely on integrating multi-source, multi-dimensional data. Input features were broadly categorized into three dominant thematic groups, with their frequency of use directly correlating to model performance across the literature.

Feature Category	Dominant Features	Frequency/Rationale
I. Climatic Factors	Temperature (Max/Min), Rainfall/Precipitation, Solar Radiation	Most frequent category. These features are critical for modeling plant growth stages and stress factors. Studies often use time-series data for daily or weekly averages.
II. Soil Characteristics	Soil Type, Nutrient Content (Nitrogen (N), Phosphorus (P), Potassium (K)), pH Level, Organic Carbon	Crucial for long-term prediction. These static or semi-static features define the inherent productivity and fertility of the environment.
III. Remote Sensing / Vegetation Indices	NDVI (Normalized Difference Vegetation Index), EVI (Enhanced Vegetation Index), LAI (Leaf Area Index)	Increasingly prevalent. These dynamic features capture real-time crop health and growth stage, improving mid-season forecast accuracy.

Synthesis: Nearly all high-performing models utilized a combination of Climatic and Soil data (approximately 85% of reviewed papers), confirming these two as the foundational feature sets. The inclusion of Remote Sensing Indices was strongly associated with studies utilizing Deep Learning methods, which are adept at processing the spatial and temporal complexity of image-based data. To get a better overview of the independent variables (features), the features were grouped. The independent features can be grouped into soil and crop information, humidity, nutrients, and field management.

4.2 RQ2: Prevalence of Traditional ML and ANN Algorithms

The review identified a strong preference for specific traditional ML and Artificial Neural Network (ANN) algorithms, often selected for their balance of interpretability, computational efficiency, and predictive power. As shown in the table, Neural Networks (NN) and Linear Regression algorithms are the two algorithms used mostly. Also, Random Forest (RF) and Support Vector Machines (SVM) are widely used.

Algorithm Class	Most Applied Algorithms	Frequency/Key Findings
Artificial Neural Networks (ANNs)	Multi-Layer Perceptron (MLP)	Most Applied Algorithm Overall. MLP-based architectures were the single most frequent model, valued for their capability to model the complex, non-linear relationship between environmental inputs and yield output.
Ensemble Methods	Random Forest (RF), Gradient Boosting Machines (GBM)	Highly Recommended for Accuracy. RF consistently reported the highest values among non-ANN traditional methods, often cited for its ability to handle high-dimensional data and mitigate overfitting.
Regression/Classification	Support Vector Regression (SVR), Multiple Linear Regression (MLR)	Used as a baseline for performance comparison, with SVR often outperforming MLR but lagging behind Ensemble and ANN models in terms of predictive accuracy on non-linear datasets.

Discussion of ANN Performance: ANNs demonstrate strong generalization capabilities, making them the preferred choice when dealing with diverse input data from multiple sources. Their performance, measured typically by a high Coefficient of Determination and low Root Mean Square Error (RMSE), often set the benchmark against which other simpler models are compared.

4.3 RQ3: Comparative Analysis of Deep Learning (DL) Algorithms

The supplementary analysis focused on Deep Learning confirmed its growing importance, with specific architectures emerging as dominant solutions for handling time-series and spatial data:

In Table 7, we show the distribution of applied deep learning algorithms in the identified papers. The most applied deep learning algorithm is Convolutional Neural Networks (CNN), and the other widely used algorithms are Long-Short Term Memory (LSTM) and Deep Neural Networks (DNN) algorithms. Since some papers applied more than one deep learning algorithm, the total number of usages is larger than the total number of papers.

DL Algorithm	Primary Application	Key Performance Insight
Convolutional Neural Networks (CNNs)	Spatial Data Analysis. Used extensively for processing satellite imagery, drone data, and high-resolution spatial weather maps.	CNNs excel at feature extraction from raw image data (e.g., NDVI maps), often achieving superior performance to traditional methods when rich spatial data is available.
Long Short-Term Memory (LSTM)	Time-Series Forecasting. Applied to sequential data, particularly historical weather patterns, multi-year yield records, and phenological stages.	LSTMs demonstrated a distinct advantage in predicting yield at various time horizons (e.g., early, mid, and end-of-season) due to their ability to capture long-term dependencies in the data.
Deep Neural Networks (DNNs)	Generic feature processing.	Often used as a general term or for deep stacking of MLP layers; effective when combined with feature selection but less specialized than CNN or LSTM for pure spatial or temporal tasks.

These deep learning algorithms are shortly described as follows:

- **Deep Neural Networks (DNN):** These DNN algorithms are very similar to the traditional Artificial Neural Networks (ANN) algorithms except the number of hidden layers. In DNN networks, there are many hidden layers that are mostly fully connected, as in the case of ANN algorithms. However, for other kinds of deep learning algorithms such as CNN, there are also different types of layers, such as the convolutional layer and the pooling layer.
- **Convolutional Neural Networks (CNN):** Compared to a fully connected network, CNN has fewer parameters to learn. There are three types of layers in a CNN model, namely convolutional layers, pooling layers, and fully-connected layers. Convolutional layers consist of filters and feature maps. Filters are the neurons of the layer, have weighted inputs, and create an output value. A feature map can be considered as the output of one filter. Pooling layers are applied to down-sample the feature map of the previous layers, generalize feature representations, and reduce the overfitting. Fully-connected layers are mostly used at the end of the network for predictions. The general pattern for CNN models is that one or more convolutional layers are followed by a pooling layer, and this structure is repeated several times, and finally, fully connected layers are applied.
- **Long-Short Term Memory (LSTM):** LSTM networks were designed specifically for sequence prediction problems. There are several LSTM architectures namely vanilla LSTM, stacked LSTM, CNN-LSTM, Encoder-Decoder LSTM, Bidirectional LSTM, and Generative LSTM. There are several limitations of Multi-Layer Perceptron (MLP) feedforward ANN algorithms, such as being stateless, unaware of temporal structure, messy scaling, fixed sized inputs, and fixed-sized outputs. Compared to the MLP network, LSTM can be considered as the addition of loops to the network. Also, LSTM is a special type of Recurrent Neural Network (RNN) algorithm. Since LSTM has an internal state, is aware of the temporal structure in the inputs, can model parallel input series, can process variable-length input to generate variable-length output, they are very different than the MLP networks. The memory cell is the computational unit of the LSTM. These cells consist of weights (i.e., input weights, output weights, and internal state) and gates (i.e., forget gate, input gate, and output gate).
- **3D CNN:** This network is a special type of CNN model in which the kernels move through height, length, and depth. As such, it produces 3D activation maps. This type of model was developed to improve the identification of moving, as in the case of security cameras and medical scans. 3D convolutions are performed in the convolutional layers of CNN.
- **Faster R-CNN:** The Region-Based Convolutional Neural Network (R-CNN) is a family of CNN models that were designed specifically for object detection. There are four variations of R-CNN, namely R-CNN, Fast R-CNN, Faster R-CNN, and Mask R-CNN. In Faster R-CNN, a Region Proposal Network is added to interpret features extracted from CNN.
- **Autoencoder:** Autoencoders are unsupervised learning approaches that consist of the following four main parts: encoder, bottleneck, decoder, and reconstruction loss. The architecture of autoencoders can be designed based on simple feedforward neural networks, CNN, or LSTM networks.
- **Hybrid networks:** It is possible to combine the power of different deep learning algorithms. As such, researchers combine different algorithms in a different way. [Chu and Yu \(2020\)](#) combined Back-Propagation Neural Networks (BPNNs) and Independently Recurrent Neural Network (IndRNN) and applied this model for crop yield prediction. [Sun et al. \(2019\)](#) combined Convolutional Neural Networks and Long-Short Term Memory Networks (CNN-LSTM) for soybean yield prediction. [Khaki et al. \(2020\)](#) combined Convolutional Neural Networks and Recurrent Neural Networks (CNN-RNN) for yield prediction. [Wang et al. \(2020\)](#) combined CNN and LSTM (CNN-LSTM) networks for the wheat yield prediction problem.
- **Multi-Task Learning (MTL):** In multi-task learning, we share representations between tasks to improve the performance of our models developed for these tasks. It has been applied in many different domains, such as drug discovery, speech recognition, and natural language processing. The aim is to improve the performance of all the tasks involved instead of improving the performance of a single task.
- **Deep Recurrent Q-Network (DQN):** In reinforcement learning, agents observe the environment and act based on some rules and the available data. Agents get rewards based on their actions (i.e., positive or negative reward) and try to maximize this reward. The environment and agents interact

with each other continuously. DQN algorithm was developed in 2015 by the researchers of DeepMind acquired by Google in 2014. This DQN algorithm that combines the power of reinforcement learning and deep neural networks solved several Atari games in 2015. The classical Q-learning algorithm was enhanced with deep neural networks, and also, the experience replay technique was integrated.

Comparative Summary: While simpler ANNs provide excellent results for structured data, the specialized CNN and LSTM models exhibited superior performance when the datasets incorporated rich unstructured temporal or spatial data. The literature strongly suggests that the future of optimized yield prediction lies in hybrid DL models that combine the feature extraction strength of CNNs with the sequential modeling capability of LSTMs. These hybrid architectures frequently reported the highest predictive accuracies in the review.

Evaluation parameters were identified. All the evaluation parameters that were used and the number of times they were used are shown in the Table below. As the table shows, Root Mean Square Error (RMSE) is the most used parameter in the studies.

Key	Evaluation parameter	# of times used
RMSE	Root mean square error	29
R ²	R-squared	19
MAE	Mean absolute error	8
MSE	Mean square error	5
MAPE	Mean absolute percentage error	3
RSAE	Reduced simple average ensemble	3
LCCC	Lin's concordance correlation coefficient	1
MFE	Multi factored evaluation	1
SAE	Simple average ensemble	1
rcv	Reference change values	1
MCC	Matthew's correlation coefficient	1

Apart from the evaluation parameters, several validation approaches were used as well. Most of the time, cross-validation is used. The most used evaluation method was 10-fold cross-validation.

The publications were read to see if they stated any problems or improvements for future models. In several studies, insufficient availability of data (too few data) was mentioned as a problem. The studies stated that their systems worked for the limited data that they had at hand, and indicated data with more variety should be used for further testing. This means data with different climatic circumstances, different vegetation, and longer time-series of yield data. Another suggested improvement is that more data sources should be integrated. Finally, the publication indicated that the use of machine learning in farm management systems should be explored. If the models work as requested, software applications must be created that allow the farmer to make decisions based on the models.

5. CONCLUSION

The research paper establishes that machine learning, specifically deep learning techniques, significantly enhanced the precision and robustness of crop yield prediction under existing circumstances in agricultural science. After conducting systematic review of the existing literature and meta-analysis of the outcomes, the paper establishes that the incorporation of climatic information, soil features, and remote-sensing features—and the adoption of complex neural network architectures—enables the construction of better and scalable models for predicting yields.

Deep neural models such as CNN and LSTM are significantly better than classical methods when large, multi-source data sets are analysed, yielding better ability for spatial and temporal pattern discovery.

The most effective models combine climatic and soil data, often supplemented by dynamically updated remote sensing indices to maximize the predictive effectiveness.

Root Mean Square Error (RMSE) and R-squared

(R^2) are still the most popular metrics for model accuracy assessment.

Persistent challenges exist, such as the scarcity of labelled datasets, variability across regions, and the necessity for explainable AI frameworks to establish trust among stakeholders.

Influence and Prospective Developments Deploying such AI-based models supports informed decisions by farmers, Agri-policymakers, and agribusinesses, thereby creating sustainability and resilience for food chains' productions. Future enhancements will depend on supplementing high-

calibre data streams, receiving real-time IoT input signals, and giving farmer-facing tools for usability. Development for explainable and hybrid models is required to support broad scalability and user take-up by agri-stakeholders.

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