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PREDICTIONS REGARDING CROP YIELD USINGDEEP LEARNING

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ABSTRACT

In India, conventional techniques for forecasting crop yield often overlook the complex interactions between climate factors, soil conditions, and crop varieties. However, deep learning presents a promising solution by utilizing artificial neural networks to analyze massive volumes of data and uncover hidden patterns. This study investigates deep learning models' efficacy in forecasting crop yields across different agroecosystems in India. Covering several deep learning architectures, especially recurrent and convolutional neural networks, was essential to assess their ability to learn from historical yield data, meteorological data, soil parameters, and remote sensing images.

The research has uncovered the significance of choosing models that are customized especially for the context to achieve optimal yield prediction. Although no single model has emerged as a universal champion, certain models have shown outstanding performance when used with specific crops. The Random Forest model has proven to be versatile and effective in predicting yields for diverse crops such as chilli, cotton, and maize. Conversely, Deep Neural Networks have exhibited promising results in predicting oil palm yields, demonstrating their potential for additional investigation with other crops.

To effectively predict crop yield, it is crucial to carefully consider the specific context, including the characteristics of the data, desired level of accuracy, and the computational resources available. The evaluation of models according to their past performance with similar crops and data becomes essential for making the best selection. As a result, this study lays the foundation for developing more precise and region-specific models for yield prediction. By doing so, it empowers farmers to make well-informed decisions regarding crop selection, resource allocation, and risk management. Ultimately, this advancement can significantly enhance agricultural productivity and food security in India.

Keywords— Deep learning, Convolutional neural networks, recurrent neural networks, and crop yield prediction, historical yield data, meteorological data, soil parameters,
remote sensing images.

I. Introduction

In India, agriculture remains among the oldest enterprises. Different methods of cultivation are used throughout various regions. But as time has gone on, so too have these techniques, due to shifts in societal standards, technology advancements, and weather and climate conditions. Among the primary suppliers of rice, wheat, cotton, sugar, milk, and horticulture worldwide is India. Since grains make up the majority of food in both India and the global community over large. Consequently, the demand for food grains globally creates a favourable environment for export of Indian products. Grain production, including wheat, rice, buckwheat, and barley, represents one among the major agricultural contributions made by the nation.

One subset of intelligent automation is called deep learning, which is essentially a three- or multi-layer neural network. These neural networks attempt to mimic the behaviour of the human brain - although it is far from its capabilities - allowing it to "learn" from a lot of information. A single-layer neural network is still capable of prediction, but additional hidden layers can help correct and tune. Its ability to analyse vast amounts of data, identify hidden patterns, and make accurate predictions makes it ideally suited for tackling thecomplexities of crop yield forecasting in India.

Revolutionizing Indian Agriculture:

Deep learning can empower Indian farmers in manyways. By analysing historical results, weather patterns, satellite imagery and the quality of soil, Models of deep learning can provide findings that are more precise and crop area estimates than traditional methods. This allows farmers to improve resource allocation, prepare the harvest window and reduce risks. Models for deep learning can extract recommendations from heterogeneous data. These insights help farmers in crop selection, planting planning, water and fertilizer use, management of diseases and pests, etc. It can guide people to decide on matters with knowledge and fix products. Deep learning can detect early signs of threats such as pests, drought, or floods. This situation causes farmers to take steps to reduce and protect their crops. Models for deep learning can be specifically trained to use photos to identify agricultural illnesses captured by CNNs, drones, or smartphones. Early detection of diseases enables timely intervention and reduces the impact on crops.

I. METHODOLOGY

Finding research papers on agricultural prediction of yield with machine learning techniques involved a thorough search process entailing exploration of academic databases, journals, and repositories to identify relevant publications. Factors such as recent publication, crop diversity, and varied approaches played a role in selecting the papers.

To comprehend the documents, delving into each paper deeply was necessary. The goal was to understand the specific crops targeted for yield prediction in each study. The methodology employed, including the types of machine learning algorithms used, feature selection, model development, and evaluation methods, was carefully examined. Note was also taken of the outputs and strategies for machine learning that showed the most promising resultsin predicting agricultural yields.

Putting everything together, an organized table or framework was produced to organize and summarize the findings. This table allowed for the documentation of the crops focused on in each publication, listing the various machine learning methods employed, and highlighting the emergence of machine learning algorithms as the most successful for predicting agricultural yields across multiple articles.

To obtain a deeper comprehension, a comparison analysis was performed to identify differences in methodology across different studies. Patterns or connections between specific machine learning algorithms and their capacity to forecast crop yields were also sought. Additionally, any limitations or obstacles encountered in the methodology or datasets used in the publications were reported.

Based on all of the data, the study's findings were presented, highlighting the machine learning algorithms that showed the greatest promise for predicting agricultural output.Proposing future research directions and outlined potential enhancements and areas of focus to improve crop production prediction using machine learning.

After all the research and analysis, the paper was written. Following a structured approach, a brief summary of the literature, methods, findings, discussion, and conclusion were all presented. To ensure the quality of the work, feedback was sought from peers, mentors, and field experts, incorporating their criticisms and suggestions for improvement.

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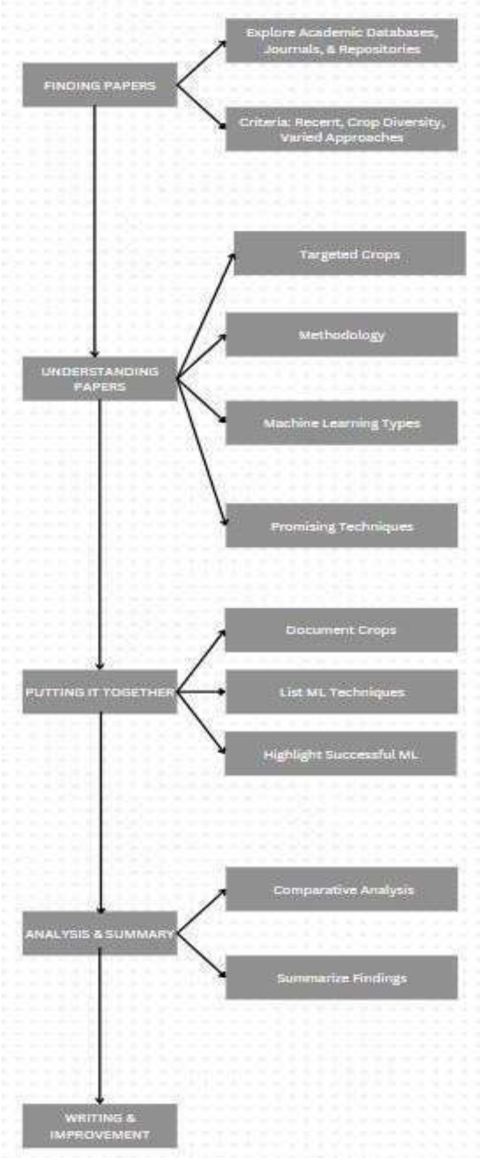

TABLE I :
TABLE OF ANALYSIS

Serial number	Aim	Method Used	Conclusion
1	Paddy yield prediction[1]	Regression using Decision Trees Forest Regression at Random Linear Regression K Nearest Neighbour Regression Xgboost Regression Support Vector Regression	With 98.77% accuracy, KNN regression is best; the Support Vector Regression technique came in second.
2	rice yield Prediction[2]	CNN (Convolutional Neural Network)	Accuracy with R-squared of 0.91
3	Paddy Yield Prediction[3]	MLR-LSTM MLR RF SVM LSTM	MLR-LSTM.
4	rice maize seed cotton yams bananas cassava[4]	tree model K-Nearest Neighbor model logistic regression	discovered that the decision tree model exhibits good performance, with a 95.3% coefficient of determination (R-squared 2).
5	Maize Crop Yield Prediction	Random forest Linear regression	Random Forest Regressor model gave best results
6	Maize Yield Predictions Using Machine Learning[5]	random forest cubist single-layer perceptron feedforward neural networks support vector regression with linear and radial basis function kernels Gaussian process regression k-nearest neighbors	The most accurate method for forecasting maize production was Gaussian process regression (GPR). The second choice is Random Forest
7	Irish Potato Maize[6]	Random Forest Polynomial Regression Support Vector Regressor.	Random forest gave best.

8	Chillie and Cotton[7]	Bayes Net Naive Bayes Classifier Logistic Multilayer Perception Simple Logistic IBK KSTAR LWL Ada Boost M1 Regression Decision Table Hoeffding Tree J48 Random Forest Random Tree	the following are best choice: Bayes Net - 99.59 Naïve Bayes Classifier - 99.46 Random Forest - 99.46 Hoeffding Tree - 99.46
9	Cotton Sugarcane[8]	LR- proposed Decision Trees K-NN	LR-proposed regression with accuracy of 99% and 98% respectively
10	Sugarcane yield Prediction[9]	Random Forest Artificial neural network (ANN) Multiple linear regression (MLR)	RF regression showed better performance
11	Sugarcane yield Prediction[10]	GBR (gradient boosting regression) SVR(support vector regression) RFR(random forest regression) XGB(eXtreme gradient boostingregression)	GBR provided higher accuracy
12	Wheat yield prediction[11]	Linear Regression (LR) Decision Tree (DT) SVM (or) support vector machine Ensemble Learning (EL) Gaussian Process Regression (GPR)	GPR model performs the best
13	Tomato[12]	ARD Regn + SVR ARD Regr Huber Regr. + SVR Huber Regr. ARD Regn + Huber Regn ARD Regr + Random Forest + SVR ARD Regr + Decision Tree Huber Regn + Theil-Sen Regn SVR + Theil-Sen Regr. ARD Regr- + Random Forest	When ARD regression and SVR were combined, the highest accurate results were produced.

14	Soybean[13]	XGBoost machine learning (ML) algorithm Convolutional Neural Networks (CNN)-Deep Neural Networks (DNN) CNN-XGBoost, CNN-Recurrent Neural Networks (RNN) CNN-Long Short Term Memory (LSTM).	CNN-DNN model outperforms other models giving best results(R-squared of 0.87),The second-best result was achieved by the XGBoost model
15	Groundnut Crop Production [14]	multiple linear Regression Regression Tree Artificial Neural Network(ANN) K-nearest Neighbor	When it comes to groundnut crops, the KNN algorithm performs better than other algorithms
16	Peanut yield prediction[15]	Support vector regressor Decision tree Random Forest Extra tree classifier AdaBoost XGBoost Multilayer perceptron neural network	XGBoost performed best with (R-squared of 86.43 %), then RF with (R-squared of 82.69%) and SVR with (R-squared of 81.26 %).
17	Predicting Groundnut Yield[16]	Levenberg–Marquardt Bayesian Regularization Scaled Conjugate Gradient	Levenberg–Marquardt gave best results outperforming the BR and SCG.
18	Soybean yield prediction[17]	Partial Least Squares Regression (PLSR) Random Forest Regression (RFR) Support Vector Regression (SVR) input-level feature fusion based DNN (DNN-F1) intermediate-level feature fusion based DNN (DNN-F2)	DNN-F2 with (R-squared of 0.720)
19	prediction of soybean yields[18]	LASSO K-nearest neighbor random forest support vector regression Stacking	stacking model
20	Finger Miller yield prediction	Multiple linear Regression	The accuracy of the selected regression model is high.
21	Winter wheat yield prediction[19]	Linear Regression (LR) Decision Tree (DT) Support Vector Machine (SVM) Ensemble Learning (EL) Gaussian process regression (GPR)	GPR model performed the best
22	Ragi and Ground nut yeild prediction[20]	Modified Hendricks and Scholl method	Hendricks and Scholl used to improve yield estimates of ragi and groundnut at mid-crop (F2) and pre-harvest stage

23	Corn yeild prediction[21]	UAV data acquisition and processing Linear Regression (LR) Deep Neural Networks(DNN) Systematic vascular resistance(SVR) Radio frequency(RF)	when UAV-derived VIs combined with machine learning models produces accurate results for corn yield prediction
24	Oil-Palm Yield Prediction[22]	Linear Regression (LR) XGBoost Support Vector Regression (SVR) Random Forest (RF) Deep Neural Network (DNN)	DNN achieved the best performance
25	Rice Yield Prediction[23]	Decision Tree (DTR) Random Forest (RF) Linear Regression (LR) K Nearest Neighbour (KNN) Xgboost Regression Support Vector Regression (SVR)	KNN got the best with 98.77% accuracy
26	Paddy yield prediction[24]	Support Vector Regression (SVR) General Regression Neural Networks (GRNN) Radial Basis Functional Neural Networks (RBFNN) Back-Propagation Neural Networks (BPNN)	GRNN predicted the yield more precisely
27	Soybean yield prediction[25]	Multiple Linear Regression (MLR) Support vector regression (SVR) Random Forest regression(RFR)	Random forest Regression performed the best
28	Rice yield Prediction[26]	Linear Regression (LR) Polynomial Regression Support Vector Regression(SVR)	Support Vector Regression (SVR)
29	Rice yield Estimation[27]	Random Forest in-combination with the multilayer Feedforward Neural Network (RaNN)	When compared to other ML Algorithms like MLR, RF, SVR, DT, ANN, RaNN has listed a better prediction accuracy.
30	lentil genotypes[28]	multivariate adaptive regression spline (MARS) support vector regression (SVR) artificial neural network (ANN) MARS-ANN MARS-SVR	MARS-based hybrid models are best compared to individual models such as MARS, SVR and ANN.

I. CONCLUSIONS AND DISCUSSIONS

In conclusion,

Conducting a study comparing the performance of several machine learning approaches in predicting crop yields across various crops and datasets, no single model emerged as the ultimate champion. However, valuable insights were gained regarding the importance of selecting context-specific models.

Here are the key takeaways from the study:

- Crop-Specific Model Choice: When predicting crop yield, the optimal model varies greatly depending on the specific crop. It's crucial to take into account the unique characteristics of each crop and the availability of data when selecting a model.
- Adaptability of Random Forest: Random Forest showed strong performance across multiple crops like chilli, cotton, and maize. This highlights its versatility and effectiveness in tackling diverse yield prediction tasks.
- Rising Potential of Deep Learning: The study revealed promising results for predicting oil palm yield using Deep Neural Networks (DNNs). This indicates the increasing value of DNNs in this field and demands for further examination other crops.
- Contextual Evaluation: To decide upon the best model, it is essential to carefully consider the specific context, including data characteristics, desired level of accuracy, and available computational resources. Thoroughly evaluating various models According to their previous performance with similar crops and data is crucial for optimal selection.

REFERENCES

[1] Wilson, Akhil, Raji Sukumar, and N. Hemalatha. "Machine learning model for rice yield prediction using KNN regression." *agriRxiv* 2021 (2021): 20210310469.

[2] Han, Xiao, et al. "Research on rice yield prediction model based on deep learning." Computational Intelligence and Neuroscience 2022 (2022).

[3] Sathya, P., and P. Gnanasekaran. "Paddy Yield Prediction in Tamilnadu Delta Region Using MLR-LSTM Model." *Applied Artificial Intelligence* 37.1 (2023).

[4] Cedric, Lontsi Saadio, et al. "Crops yield prediction based on machine learning models: Case of West African countries." *Smart Agricultural Technology* 2 (2022): 100049.

[5] Croci, Michele, et al. "Dynamic Maize Yield Predictions Using Machine Learning on Multi-Source Data." *Remote Sensing* 15.1 (2022): 100.

[6] Kuradusenge, Martin, et al. "Crop yield prediction using machine learning models: case of Irish potato and maize." *Agriculture* 13.1 (2023): 225.

[7] Elbasi, Ersin, et al. "Crop prediction model using machine learning algorithms." *Applied Sciences* 13.16 (2023): 9288.

[8] Patil, Ashwini I., Ramesh A. Medar, and Vinod Desai. "Crop Yield Prediction Using Machine Learning Techniques." *International Journal of Scientific Research in Science, Engineering and Technology* (2020): 312-315.

[9] Maldaner, Leonardo Felipe, et al. "Predicting the sugarcane yield in real-time by harvester engine parameters and machine learning approaches." *Computers and Electronics in Agriculture* 181 (2021): 105945.

[10] Nihar, Ashmitha, N. R. Patel, and Abhishek Danodia. "Machine-Learning-Based Regional Yield Forecasting for Sugarcane Crop in Uttar Pradesh, India." *Journal of the Indian Society of Remote Sensing* 50.8 (2022): 1519-1530.

[11] Wang, Ying, Wenjuan Shi, and Tianyang Wen. "Prediction of winter wheat yield and dry matter in North China Plain using machine learning algorithms for optimal water and nitrogen application." *Agricultural Water Management* 277 (2023): 108140.

[12] Darra, Nicoleta, et al. "Can Satellites Predict Yield? Ensemble Machine Learning and Statistical Analysis of Sentinel-2 Imagery for Processing Tomato Yield Prediction." *Sensors* 23.5 (2023): 2586.

[13] Oikonomidis, Alexandros, Cagatay Catal, and Ayalew Kassahun. "Hybrid deep learning-based models for crop yield prediction." *Applied artificial intelligence* 36.1 (2022): 2031822.

[14] Shah, Vinita, and Prachi Shah. "Groundnut crop yield prediction using machine learning techniques." *International Journal of Scientific Research in Computer Science, Engineering and Information Technology* 3.5 (2018).

[15] Shahi, Tej Bahadur, et al. "Peanut yield prediction with UAV multispectral imagery using a cooperative machine learning approach." *Electronic Research Archive* 31.6 (2023): 3343-3361.

[16] Sajindra, Hirushan, et al. "An Artificial Neural Network for Predicting Groundnut Yield Using Climatic Data." *AgriEngineering* 5.4 (2023): 1713-1736.

[17] Maimaitijiang, Maitiniyazi, et al. "Soybean yield prediction from UAV using multimodal data fusion and deep learning." *Remote sensing of environment* 237 (2020): 111599.

[18] LI, Qian-chuan, et al. "Ensemble learning prediction of soybean yields in China based on meteorological data." *Journal of Integrative Agriculture* 22.6 (2023): 1909-1927.

[19] Wang, Ying, Wenjuan Shi, and Tianyang Wen. "Prediction of winter wheat yield and dry matter in North China Plain using machine learning algorithms for optimal water and nitrogen application." *Agricultural Water Management* 277 (2023): 108140.

[20] Rajegowda, M. B., et al. "Ragi and groundnut yield forecasting in Karnataka–statistical model." *Journal of Agrometeorology* 16.2 (2014): 203-206.

[21] Kumar, Chandan, et al. "Multi-Stage Corn Yield Prediction Using High-Resolution UAV Multispectral Data and Machine Learning Models." *Agronomy* 13.5 (2023): 1277.

[22] Ang, Yuhao, et al. "Oil palm yield prediction across blocks from multi-source data using machine learning and deep learning." *Earth Science Informatics* 15.4 (2022): 2349-2367.

[23] Wilson, Akhil, Raji Sukumar, and N. Hemalatha. "Machine learning model for rice yield prediction using KNN regression." *agriRxiv* 2021 (2021): 20210310469.

[24] Joshua, Vinson, Selwin Mich Priyadharson, and Raju Kannadasan. "Exploration of machine learning approaches for paddy yield prediction in eastern part of Tamilnadu." *Agronomy* 11.10 (2021): 2068.

[25] Mohite, J. D., et al. "Soybean Crop Yield Prediction by Integration of Remote Sensing and Weather Observations." *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences* 48 (2023): 197-202.

[26] Rahman, Tasnia, and Sakifa Aktar. "Machine Learning Approaches to Predict Rice Yield of Bangladesh." *2022 International Conference on Innovations in Science, Engineering and Technology (ICISET)*. IEEE, 2022.

[27] Lingwal, Surabhi, Komal Kumar Bhatia, and Manjeet Singh. "A novel machine learning approach for rice yield estimation." *Journal of Experimental & Theoretical Artificial Intelligence* (2022): 1-20.

[28] Das, Pankaj, et al. "Crop Yield Prediction Using Hybrid Machine Learning Approach: A Case Study of Lentil (Lens culinaris Medik.)." *Agriculture* 13.3 (2023): 596.