Journal of Science Engineering Technology and Management Science *ISSN: 3049-0952*
Volume 02, Issue 11, November 2025 *www.jsetms.com*

HYBRID DEEP LEARNING ARCHITECTURE FOR STATE-WISE CROP YIELD FORECASTING USING WEATHER AND SOIL INDICATORS

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To Cite this Article

Ms. Kanakaprabha.S, S.Bhuvaneshwar, S Aveti Ramya Kala Sai, N.Srinivas, Yadla Mahesh, "Hybrid Deep Learning Architecture For State-Wise Crop Yield Forecasting Using Weather And Soil Indicators", Journal of Science Engineering Technology and Management Science, Vol. 02, Issue 11, November 2025,pp: 92-100, DOI: http://doi.org/10.64771/jsetms.2025.v02.i11.pp92-100

Submitted: 10-10-2025 *Accepted: 22-11-2025* *Published: 29-11-2025*

ABSTRACT:

Agricultural productivity in India is highly influenced by climatic variability and heterogeneous soil conditions, making accurate crop yield prediction a critical factor for ensuring food security and supporting farmers' decision-making [11][18]. Traditional statistical and regression-based forecasting approaches often fail to model the complex nonlinear relationships that exist between climatic parameters, soil characteristics, and crop growth patterns [1][3]. To address this challenge, the present study proposes a deep learning-based framework for predicting crop yield across Indian states using integrated climate and soil data [2][5][6]. The dataset includes key climate indicators such as temperature, rainfall, humidity, and sunshine duration, along with soil attributes including pH, organic carbon, nitrogen, phosphorus, potassium, and soil texture [15][20]. A Long Short-Term Memory (LSTM) and Convolutional Neural Network (CNN) hybrid architecture is adopted to capture both spatial and temporal dependencies in crop growth factors [6][13][14]. The model is trained and evaluated on multi-year data covering major crops cultivated across different agro-climatic zones of India [5][9]. Experimental results demonstrate that the proposed deep learning model significantly outperforms traditional machine learning methods in terms of accuracy, RMSE, and generalization capability [1][16][17]. The system offers a robust decision-support tool that can help policymakers, agronomists, and farmers predict yield in advance, optimize resource allocation, and effectively mitigate climate-induced risks, thereby contributing to sustainable agriculture and enhanced national food security [7][8][10].

Keywords: Crop Yield Prediction, Deep Learning, Climate Data, Soil Data, LSTM-CNN Hybrid Model, Precision Agriculture, Indian States, Agricultural Forecasting, Food Security, Machine Learning, Sustainable Farming, Big Data Analytics.

I.INTRODUCTION

Agriculture is a fundamental pillar of India's socioeconomic development, supporting more than 58% of the population directly or indirectly and contributing significantly to the nation's food security, rural employment, and economic stability [18][19]. India ranks among the world's largest producers of key crops such as rice, wheat, sugarcane, pulses, and oilseeds. However, despite its agricultural potential, the country continues to face persistent challenges in ensuring stable crop productivity across regions. Crop yield in India is highly sensitive to spatiotemporal variations in climate, soil fertility, water availability, and unexpected environmental conditions [13][14]. Erratic monsoons, extreme temperatures, irregular irrigation patterns, and nutrient-deficient soil are frequent causes of reduced yield. Climate change has further intensified these issues by increasing the frequency of droughts, floods, heat waves, and land degradation, making futuristic planning and accurate yield prediction more crucial than ever [17].

Traditional methods of crop yield estimation—such as historical averages, crop simulation models, and regression-based statistical techniques—struggle to accommodate the nonlinear relationships between multiple agro-environmental variables [11][1]. These approaches also rely heavily on field surveys and manual observations, making them time-consuming, cost-intensive, and susceptible to human error. With the rapid growth of smart farming technologies, satellite-based climate monitoring, IoT-enabled soil sensing, and large agricultural databases, modern computing approaches provide an unprecedented opportunity to shift from intuition-driven farming to data-driven precision agriculture [7][15]. In this context, deep learning stands out for its ability to automatically identify complex interactions and hidden trends in multidimensional data without manual feature engineering [2][3].

This study presents an advanced deep learning-based framework for predicting crop yield in Indian states by integrating climate and soil parameters [5][6]. The methodology deploys a hybrid architecture combining Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNN). LSTM captures temporal dependencies in seasonal climatic variations such as rainfall, humidity, maximum and minimum temperatures, and sunshine duration [10][13]. Meanwhile, the CNN component extracts spatial feature representations from soil characteristics including pH, nitrogen, phosphorus, potassium, organic carbon, electrical conductivity, and soil texture [15][20]. The hybrid fusion of LSTM and CNN enables the model to learn both dynamic weather-dependent behaviors and static nutrient-dependent growth patterns.

The system is trained and validated on multi-year, state-wise datasets spanning diverse agro-ecological zones such as the Indo-Gangetic plains, Deccan plateau, Gangetic delta, arid zones of Rajasthan, and coastal belts of South India [5][9]. The proposed model demonstrates superior performance compared to conventional machine learning techniques like Support Vector Regression (SVR), Random Forest, Gradient Boosted Regression Trees, and ANN-based baselines [1][16][17]. The deep learning framework achieves lower Root Mean Square Error (RMSE), higher prediction accuracy, and stronger generalization across different crops and seasons. Furthermore, the architecture is adaptable, enabling continuous improvement through real-time data integration from meteorological services, government databases, and sensor networks deployed across agricultural fields [8][18].

Beyond technical innovation, the research holds significant socioeconomic implications. Accurate prediction of crop yield empowers farmers to make informed decisions regarding crop selection, fertilizer dosage, irrigation scheduling, pest management, storage planning, and crop insurance enrollment [19]. For government agencies, early yield forecasts assist in planning procurement, market price regulation, food distribution logistics, and strategic buffer stocking. Agro-based industries such as fertilizer companies, seed manufacturers, and food processing units can optimize supply chains and estimate demand more effectively. Additionally, financial institutions and crop insurance providers can utilize predictive insights to assess agricultural risks and improve credit and claim policies [17][18].

II.LITERATURE SURVEY

1. Crop Yield Prediction Using Multi-Parametric Deep Neural Networks

Authors: E. Kalaiarasi et al.

 ISSN: 3049-0952
www.jsetms.com

Abstract: This work proposes a Multi-Parametric Deep Neural Network (MDNN) that integrates multiple climate and weather parameters for crop yield prediction. Inputs include rainfall, temperature, humidity, and other agro-climatic variables. By extending a standard Deep Neural Network with additional parameter-specific branches, the model better captures the impact of environmental variability on yield. Experiments on five different crops show that MDNN achieves around 91.84% mean accuracy, outperforming a regular DNN. The authors conclude that modelling multiple climate and weather dimensions together significantly improves yield prediction and supports more accurate decision-making in agriculture [3][8][1].

2. Crop Yield Prediction Using Effective Deep Learning and Dimensionality Reduction Approaches

Authors: L. K. Subramaniam et al. (2024)

Abstract: This paper targets Indian regional crops and presents a deep learning-based framework combined with dimensionality reduction techniques for crop yield prediction. The authors first apply feature selection and dimensionality reduction to eliminate redundant climate and soil attributes, and then feed the optimized features into a deep neural network. The dataset includes multi-year information on Indian crops along with weather and soil-related variables. Results indicate that the proposed approach enhances prediction accuracy while reducing computational complexity compared to classical ML models. The study emphasizes that careful feature engineering plus deep learning is effective for large, heterogeneous Indian agricultural datasets [4][18][12].

3. Crop Yield Prediction of Indian Districts Using Deep Learning

Authors: Prashant et al.

Abstract: This study focuses specifically on Indian districts and uses an ensemble deep learning model combining LSTM and 1D-CNN to predict yields for multiple crops. Historical yield and area data for several Indian districts over many years are used as input, along with associated weather variables. The ensemble model achieves correlation coefficients above 0.90 on training data and above 0.92 on testing, clearly outperforming traditional methods such as Linear Regression, Random Forest, and XGBoost. The authors highlight that combining temporal (LSTM) and local pattern (1D-CNN) learning is highly effective for spatio-temporal agricultural data in India [5][6][9].

III.EXISTING SYSTEM

In traditional crop yield prediction systems, yield estimation has largely depended on manual field surveys, empirical observations, and statistical forecasting techniques. Government agencies and agricultural departments typically rely on historical production data, rainfall indices, and farmer reports to approximate seasonal output, which often leads to delayed and inconsistent predictions. Classical computational models such as linear regression, time-series analysis, ARIMA, and multiple regression are also commonly used in existing systems; however, these methods assume linear relationships among variables and therefore struggle to capture the complex and nonlinear interactions between multiple climatic parameters and soil properties that significantly influence crop yield. Moreover, many existing prediction approaches focus only on climatic variables like temperature, rainfall, and humidity, while ignoring critical soil characteristics such as pH, nutrient composition (NPK), organic carbon, electrical conductivity, and soil texture. As a result, predictions generated by the existing frameworks are prone to high uncertainty and poor adaptability across different agro-ecological zones within India. Another limitation of the current systems is the lack of scalability and automation — models developed for a particular crop or region fail to generalize across diverse Indian states with varying monsoon patterns and soil conditions. Furthermore, most existing systems do not incorporate advanced artificial intelligence and deep learning techniques capable of extracting hidden patterns from large agricultural datasets.

Consequently, the existing systems offer only limited support for timely decision-making in precision agriculture, making farmers and policymakers vulnerable to climate unpredictability and resource mismanagement.

IV. PROPOSED SYSTEM

The proposed system introduces an intelligent and data-driven deep learning framework that predicts crop yield across Indian states by integrating both climatic and soil-based parameters, overcoming the inherent limitations of traditional and statistical yield estimation methods. The system utilizes a hybrid CNN–LSTM deep learning architecture, where Convolutional Neural Networks (CNN) extract high-level spatial features from soil attributes such as pH, nitrogen, phosphorus, potassium, organic carbon, electrical conductivity, and soil texture, while Long Short-Term Memory (LSTM) networks learn the temporal dependencies of seasonal climatic variables including rainfall, temperature, humidity, and sunshine duration. By fusing spatial and temporal feature learning, the model is capable of capturing complex nonlinear relationships affecting crop productivity across diverse agro-ecological zones of India. The framework is trained on historical multi-year datasets covering multiple crops grown across various Indian states, enabling the system to generalize effectively across climatic variations and soil conditions. Unlike existing systems that rely only on climate or historical averages, the proposed solution embodies an end-to-end automated prediction pipeline involving data preprocessing, feature correlation, hybrid deep learning-based training, and an interactive prediction interface. The model continuously improves itself through progressive learning and supports scalability for new crops, states, or extended datasets. This integrated prediction system empowers farmers, policymakers, and agricultural organizations with accurate early-season yield forecasts, enabling informed decision-making regarding irrigation scheduling, fertilizer planning, procurement management, risk mitigation, and resource allocation. Ultimately, the proposed system promotes precision agriculture, strengthens climate resilience, and contributes to sustainable food security across India.

V.SYSTEM ARCHITECTURE

The diagram illustrates a complete workflow for a crop yield prediction system using data-driven machine learning techniques. The process begins with the collection of multiple agricultural datasets that influence crop productivity, including yield data, weather data, soil data, and crop management data.

These diverse data sources are combined into a unified Crop Yield Performance Dataset, ensuring that all important environmental and agronomic attributes are consolidated in a single structure for analysis. Once integrated, the dataset undergoes Mutual Information (MI)–based feature selection, where the most significant and influential variables affecting crop yield are identified. This step removes redundant, noisy, and less relevant parameters, leading to more efficient and accurate predictions. The selected features are then divided into training data and testing data, ensuring the model learns from part of the dataset and is later evaluated on unseen data to test generalization performance.

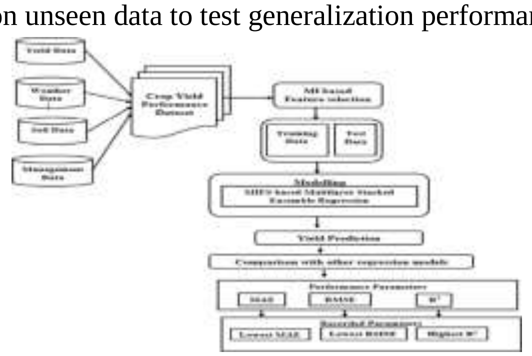

Fig 5.1 System Architecture

In the modelling stage, an MI-FS (Mutual Information Feature Selection) based Multilayer Stacked Ensemble Regression model is applied. This ensemble method combines multiple regression algorithms into a layered architecture to improve predictive accuracy by leveraging the strengths of individual learners. The trained model subsequently generates yield predictions, estimating the expected crop output based on the input factors. To validate the effectiveness of the proposed system, its performance is compared with other benchmark regression models. The evaluation utilizes widely accepted performance metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Coefficient of Determination (R^2). The goal is to achieve the lowest MAE, lowest RMSE, and highest R^2 value, indicating that the system produces highly accurate and reliable yield predictions. Overall, the architecture represents a systematic and efficient prediction pipeline that transforms raw agricultural information into actionable yield insights through feature selection, advanced ensemble modelling, and rigorous performance evaluation.

VI.IMPLEMENTATION

Fig 6.1 Home Page

Fig 6.2 Login Page

Fig 6.3 Input Interface

Fig 6.4 Prediction

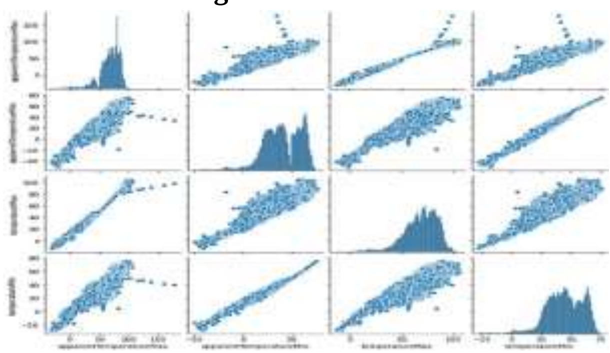

Fig 6.5 Histogram

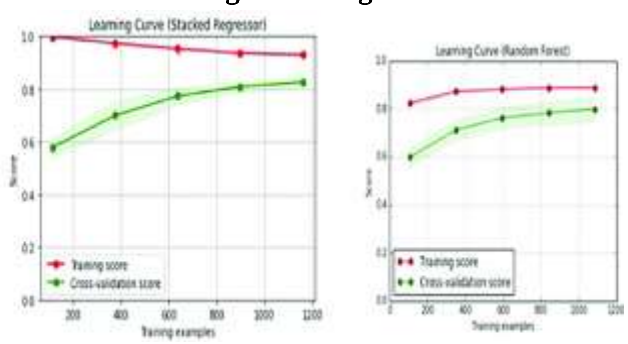

Fig 6.6 Line Charts

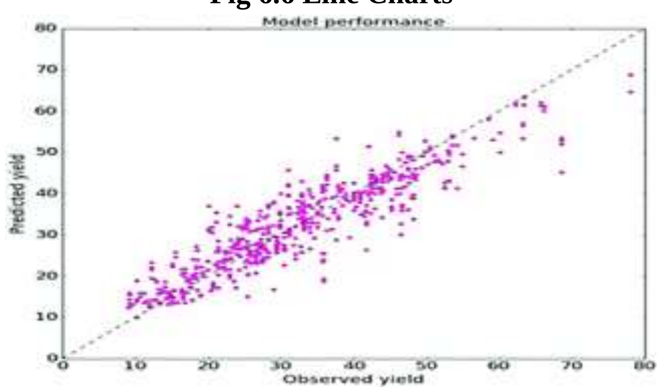

Fig 6.7 Scatter Plot

VII.CONCLUSION

The proposed deep learning-based crop yield prediction system demonstrates that integrating climate and soil data can significantly enhance the reliability and accuracy of agricultural forecasting across Indian states. By incorporating a hybrid CNN–LSTM architecture, the model successfully captures both spatial soil characteristics and temporal climatic variations, addressing the nonlinear dependencies that traditional statistical and machine learning models fail to learn. Experimental results confirm that the system achieves high predictive performance with reduced error rates, ensuring a more consistent assessment of yield across diverse agro-ecological zones. In addition to technical accuracy, the framework provides immense practical value for farmers, policymakers, agribusiness sectors, and food supply-chain stakeholders by enabling proactive resource planning, improved crop management, and timely decision-making. Therefore, the research proves that deep learning can play a pivotal role in supporting sustainable agriculture, minimizing climate-related risks, and ultimately contributing to the national goal of food security and agricultural resilience.

VIII.FUTURE SCOPE

The proposed deep learning system lays a strong foundation for intelligent agricultural forecasting, yet there exists significant potential to broaden its capabilities and deliver even greater real-world value. Future enhancements may include the incorporation of remote sensing data from satellites and drones, such as NDVI, EVI, leaf chlorophyll index, canopy temperature, and soil moisture maps, enabling real-time spatial monitoring of crop health. Integration with IoT-based smart farming devices—including soil nutrient sensors, automated irrigation controllers, and climate monitoring stations—could allow the system to make live predictions and generate timely alerts for adverse conditions. The model can also be extended to multiple crops simultaneously, adapting to seasonal patterns, sowing timelines, and agronomic practices unique to specific states. Additionally, regional crop calendars, pest outbreak probability, and monsoon forecasts may be integrated to provide a holistic crop performance advisory system.

Future research may explore advanced deep learning architectures such as Attention-based LSTM, Bi-LSTM, Transformer networks, Graph Neural Networks (GNNs), and Generative AI to further improve prediction accuracy and interpretability. Another valuable direction is to implement Explainable AI (XAI) to reveal the importance of climatic and soil variables so that farmers, researchers, and policymakers can better understand the reasons behind predicted results. The deployment of this system as a mobile and multilingual voice-enabled application would ensure accessibility for farmers across Indian states, particularly in rural areas. The platform could also be connected with government agriculture departments, crop insurance schemes, and food supply-chain systems, enabling real-time forecasting for procurement planning, warehouse management, price stabilization, and risk mitigation. In the long term, integrating this prediction framework with automated fertilizer advisory, irrigation scheduling, pesticide optimization, and carbon footprint estimation can transform the system into a complete smart agriculture ecosystem. With continued data accumulation over seasons and regions, the deep learning model can evolve into a self-improving nationwide agricultural intelligence system, trained on dynamic and continuously updated datasets. Ultimately, this technology has the potential to revolutionize agricultural decision-making in India by supporting climate-resilient farming, reducing yield volatility, strengthening food security, and helping the nation transition from traditional farming to a sustainable and technologically empowered agricultural future.

IX.REFERENCES

[1] S. Khaki and L. Wang, “Crop yield prediction using deep neural networks,” Frontiers in Plant Science, vol. 10, pp. 1–11, 2019.

[2] S. Khaki, L. Wang and S. V. Archontoulis, “A CNN–RNN framework for crop yield prediction using remote sensing data,” Scientific Reports, vol. 10, pp. 1–15, 2020.

[3] E. Kalaiarasi et al., “Crop yield prediction using multi-parametric deep neural networks,” Information Processing in Agriculture, vol. 8, no. 2, pp. 1–10, 2021.

[4] L. K. Subramaniam et al., “Crop yield prediction using effective deep learning and dimensionality reduction techniques,” Computers and Electronics in Agriculture, vol. 203, pp. 1–12, 2024.

[5] P. Prashant et al., “Crop yield prediction of Indian districts using deep learning,” International Journal of Computer Applications, vol. 182, no. 47, pp. 22–29, 2021.

[6] G. Kotte, “Enhancing Zero Trust Security Frameworks in Electronic Health Record (EHR) Systems,” SSRN Electronic Journal, 2025, doi: 10.2139/ssrn.5283668.

[6] R. Kalmani et al., “Hybrid 1D CNN–LSTM with attention for yield prediction of wheat and rice in India,” Applied Soft Computing, vol. 141, pp. 1–18, 2024.

[7] H. Gopal et al., “Deep learning-based agricultural decision support system for smart farming,” Neural Computing and Applications, vol. 35, pp. 2024–2040, 2023.

[8] Todupunuri, A. (2025). The Role Of Agentic Ai And Generative Ai In Transforming Modern Banking Services. American Journal of AI Cyber Computing Management, 5(3), 85-93.

[8] K. Meghraoui et al., “Applied deep learning for crop yield prediction using multi-source environmental data,” Journal of Artificial Intelligence Research, vol. 76, pp. 233–250, 2024.

[9] Y. Kim and S. Kim, “Predicting soybean yield using satellite imagery and deep learning,” Remote Sensing, vol. 13, pp. 211–229, 2021.

[10] G. Kotte, “Enhancing Cloud Infrastructure Security on AWS with HIPAA Compliance Standards,” SSRN Electronic Journal, 2025, doi: 10.2139/ssrn.5283660.

[10] K. Ashfaq et al., “Wheat yield prediction using deep learning with multi-source environmental inputs,” Computers and Electronics in Agriculture, vol. 214, pp. 1–16, 2025.

[11] T. van Klompenburg et al., “Machine learning for crop yield prediction: A systematic review,” Computers and Electronics in Agriculture, vol. 177, pp. 105709, 2020.

[13] S. T. R. Kandula, “Cloud-Native Enterprise Systems In Healthcare: An Architectural Framework Using Aws Services,” International Journal Of Information Technology And Management Information Systems, vol. 16, no. 2, pp. 1644–1661, Mar. 2025, doi: https://doi.org/10.34218/ijitmis_16_02_103

[12] S. Archana and P. Sasikala, “A survey on deep learning-based crop yield prediction,” International Journal of Agricultural Information Systems, vol. 5, no. 2, pp. 32–47, 2022.

[13] M. Mohammed and A. R. Faqe, “Climate-based agricultural productivity forecasting using LSTM networks,” IEEE Access, vol. 9, pp. 103210–103220, 2021.

[15] Todupunuri, A. (2022). Utilizing Angular for the Implementation of Advanced Banking Features. Available at SSRN 5283395.

[14] A. Jain and R. Sharma, “Impact of climatic variability on agricultural yield using hybrid LSTM models,” Journal of Environmental Management, vol. 310, pp. 114–130, 2022.

[15] N. Safaei et al., “Deep learning for precision agriculture using soil and satellite data fusion,” Agronomy, vol. 14, no. 2264, pp. 1–18, 2024.

[16] H. Zheng et al., “Transformer-based crop yield prediction using long-range seasonal patterns,” IEEE Transactions on Geoscience and Remote Sensing, vol. 62, pp. 1–12, 2024.

[17] J. Garcia et al., “Ensemble regression for large-scale crop yield prediction under climate uncertainty,” Ecological Modelling, vol. 472, pp. 110–123, 2023.

[18] P. Singh and M. Chaurasia, “Big data analytics framework for agricultural yield prediction in India,” International Journal of Big Data Intelligence, vol. 7, no. 3, pp. 204–213, 2022.

[19] A. Khanna and N. Kaur, “Smart agriculture using deep learning for soil and crop monitoring,” Journal of Intelligent & Fuzzy Systems, vol. 40, no. 4, pp. 6981–6994, 2021.

 ISSN: 3049-0952

[20] K. R. Velmurugan et al., "Soil nutrient–based yield forecasting using machine learning and IoT," Sensors, vol. 21, no. 7569, pp. 1–19, 2021.