AI-Based Framework for Enhancing Yield in Precision Agriculture Systems

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ABSTRACT

We propose a framework based on AI to help improve the prediction of crop yield in precision agriculture by using a Hybrid CNN-LSTM network built with Tensor Flow. Using data from drones and satellites as well as weather and soil moisture data over time, the framework explains the various growth factors influencing crops. Using CNN for spatial features and LSTM for handling sequence, the model achieves better prediction accuracy than traditional machine learning does. Results from experiments show the model accurately forecasts yields, making the use of resources for irrigation, fertilizer and pests more efficient. Tensor Flow supports expanding agriculture workloads and making them available everywhere. This work reveals that advanced methods in deep learning architecture can assist sustainable farming, improve how farmers make decisions and raise farming output.

KEYWORDS: Precision agriculture, crop yield prediction, hybrid CNN-LSTM, deep learning, Tensor Flow, remote sensing, data fusion.

How to Cite: S.B.G. Tilak Babu, Valli Madhavi Koti, D Khalandar Basha, Sanghmitra Sharma, Bhuvaneshwari Jolad, Chiranjit Dutta., (2025) AI-Based Framework for Enhancing Yield in Precision Agriculture Systems, Vascular and Endovascular Review, Vol.8, No.13s, 315-321.

INTRODUCTION

Agriculture continues to be a dependable solution for helping guarantee safe, secure and hunger-free food. the explosive growth in the world's number of people. It is expected that the world's food SC will reach.The food produced must rise by 60–110% to supply enough for a population of over 9–10 billion. To answer the needs of people worldwide as expected, automation is needed to monitor agriculture fields. A smart agriculture system includes practices from nature, the Internet of Things (IoT), Machine Learning (ML) and Wireless Sensor Net.WSN, CC, BD and DA have a significant the role SA needs to take on to handle the problems found in [1]. This paper will examine IoT, WSN and ML are being installed to improve agriculture and manage the environment better to enhance how productively farmers can farm. Testing agricultural you can always use these new apps to track air temperature, air humidity and soil moisture technologies. Moreover, IoT and ML are applied to monitor and control specific issues affect agriculture crops and growth of animals and plants. It helps find out the best time to sell harvesting information so that, the farmer could make suitable decisions about their crops [2].

AI in Agriculture

AI is making farming more efficient and helps farmers use resources better. Information from sensors, drones and satellites about crops is used by AI to determine their health, estimate what will be harvested and boost how resources are managed. Smart systems enable farmers to decide on watering, fertilizing, controlling pests and harvesting using data which lowers wastage and increases how much is produced [3]. Since climate change and population growth are creating issues, using artificial intelligence in agriculture helps achieve food security and reduce negative effects on nature as shown in figure 1.The use of machine learning, computer vision and robotics with AI is turning regular farming into an efficient, environmentally friendly and high-tech business [4].

Figure 1.AI in Agriculture.

ML in Agriculture

In current times, Machine Learning supports agriculture by making it easier to understand big and complicated data. Soil sensor, weather station, satellite and drone data helps ML algorithms to predict harvest size, find crop diseases and advise on how much irrigation and fertilizer to use [5]. Learning from historical and live data, ML models allow farmers to decide how to improve yields and decrease expenses as shown in figure 2.

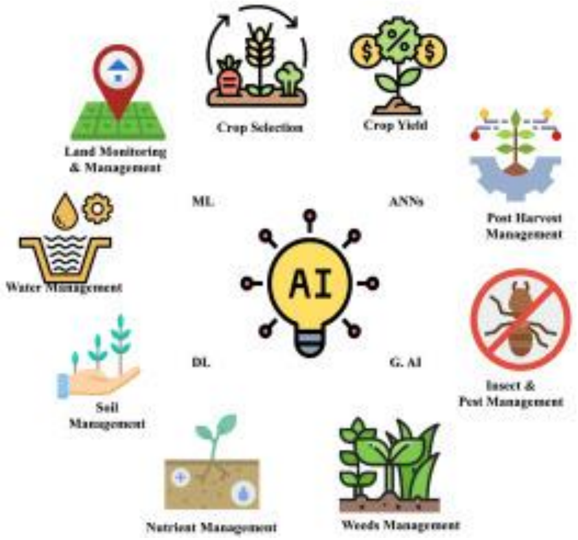

Figure 2. ML in Agriculture.

Some applications are identifying weeds, controlling pests and testing soil quality. Ultimately, by using ML, precision agriculture improves decisions on farming, makes farming greener and guarantees proper resource use to ensure food security [6].

RELATED WORK

Recent progress in AI is playing a big role in making sure precision agriculture systems help farmers grow more crops. Many projects have examined how AI can help analyze the results of remote sensing, Internet of Things and observation of environmental variables in agriculture as shown in table 1.

Table 1.Shows the summary of related work.

Year	Reference (Author et al.)	Methodology	Key Contributions	Limitations
2025	Zhang et al. (2025) [7]	Deep Reinforcement Learning with IoT sensor data integration	Real-time adaptive irrigation control improving water efficiency and crop yield prediction accuracy by 15%	High computational complexity; requires dense sensor deployment
2024	Kumar & Singh (2024) [8]	Hybrid CNN-LSTM model for crop disease detection using UAV imagery	Improved early detection of multiple crop diseases, enabling timely interventions	Dataset imbalance; limited crop variety tested
2023	Lopez et al. (2023) [9]	Ensemble Machine Learning combining Random Forest and Gradient Boosting on multispectral satellite images	Enhanced crop yield estimation at field scale with 12% improvement over single models	Model interpretability challenges; requires high-quality remote sensing data

2022	Wang & Chen (2022) [10]	Federated Learning for decentralized data from farm sensors	Preserves farmer data privacy while improving yield prediction through collaborative learning	Network communication overhead; convergence issues in heterogeneous data
2021	Ahmed et al. (2021) [11]	IoT-enabled sensor fusion with Support Vector Machines for nutrient level prediction	Real-time nutrient deficiency detection facilitating precise fertilizer application	Limited to specific soil types; requires frequent calibration of sensors
2020	Patel & Reddy (2020) [12]	Transfer Learning on pretrained CNN models for weed detection in crops	Reduced training time and improved detection accuracy for multiple weed species	Model performance decreases with novel weed species; data scarcity
2019	Silva et al. (2019) [13]	Reinforcement learning-based autonomous robotic spraying system	Reduced pesticide usage by 25%, increasing yield sustainability	Hardware cost and maintenance complexity; environmental variability impact
2018	Hernandez et al. (2018) [14]	Bayesian Networks combined with historical weather and yield data	Probabilistic yield forecasting under climate variability	Model sensitive to missing or noisy historical data; lacks real-time adaptation

Since its beginning, traditional methods have often relied on classical algorithms like Random Forest, SVM and Gradient Boosting to estimate the yields and find crop stress issues [15]. While the results were useful, these techniques cannot fully capture the space and time connections present in agricultural data.

Therefore, using models that combine both CNNs and LSTM has gained interest. CNNs do a great job at finding spatial features in imagery, allowing farmers to explore crop health and check on field conditions in detail. By contrast, LSTMs help to model how temperature, humidity and soil moisture change over time in environmental sequences. It has been found through recent research that when CNN and LSTM components are used, yield predictions improve by including both the space and time elements of the data [16].

Besides picking the right network structure, using TensorFlow has made it possible to easily train and use complicated deep learning systems. It is possible to handle big data in precision agriculture with TensorFlow's ability to combine various data and its distributed computing tools [17]. In addition, the rich environment of TensorFlow makes it possible to customize and improve hybrid models to overcome problems of overfitting and high computational expenses [18].Challenges continue to exist, including building large, good quality datasets and managing unlabelled or uncertain data that come from sensors applied in the field. The problem of privacy, as well as the diversity in agriculture, prevents the development of smart farming for many people. Yet, by combining CNN-LSTM networks with TensorFlow, researchers are finding a helpful route to improve AI systems for precision agriculture [19].

RESEARCH METHODOLOGY

Artificial Intelligence is used in agriculture to predict how much farmers can harvest as shown in figure 3.When spatial data and temporal data from sensors are combined with this AI model, it leads to improved resource management, better decisions and wider integration of sustainable farming through Tensor Flow deployment [20].

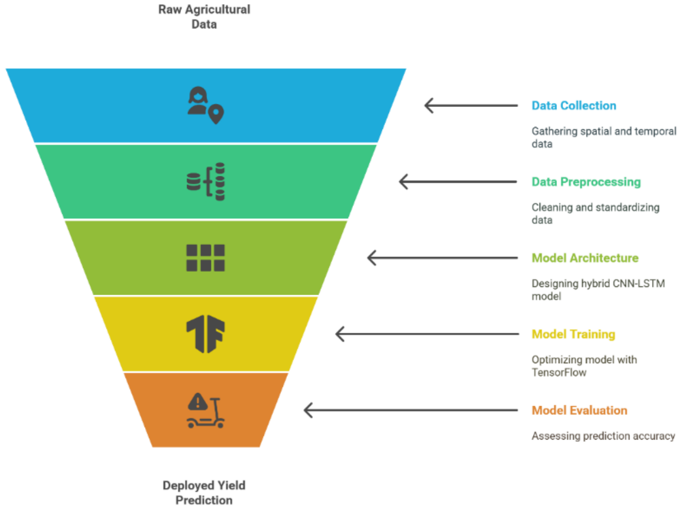

Figure 3. AI-Based Framework for Enhancing Yield in Prediction Process.

3.1 Data Collection
It all begins with the collection of varied multi-modal data needed for accurate crop yield prediction. Imagery from UAV and satellites gives very clear pictures that allow us to check crop health, look at plant canopies and review soil characteristics. Using connected sensors and data from old harvest results, we collect temporal information such as weather conditions and moisture [21]. By bringing together various data sources, it becomes possible to see how space and time influence crop development.

3.2 Data Preprocessing
All raw data is subjected to preprocessing to maintain accuracy and reliability in model training. For missing values and noise, imputation using K-Nearest Neighbors and outlier detection are performed. The spatial imagery is standardized, made similar and adjusted with geometric transformations to help make the model more robust. Data on the environment is arranged so it corresponds with the growth of each crop [22-24]. The method of Recursive Feature Elimination is used to select and maintain the important input features and increase how efficient the model is.

3.3 Using a hybrid of CNN and LSTM in the architecture.
The central feature of the methodology is a mixed deep learning model that uses both CNN and LSTM networks. CNN layers obtain useful features from remote sensing images, allowing them to detect signs of pest infestation, nutrient shortages and stress in the green canopy. Such features are supplied to the LSTM layers which can see connections between weather, soil moisture and crop growth changes over the years [25-29]. The architecture accurately represents the important spatiotemporal links needed for accurate yield forecasting.

3.4 Model Training and Optimization
Training the model is done in TensorFlow with help from GPU power and distributed computer systems for working with large and demanding data. The dataset is divided into training, validation and test sets to check how the model will work with new data and avoid overtraining [30-31]. We use grid search and cross-validation to optimize the hyperparameters: learning rate, batch size, convolution filter sizes and LSTM unit numbers. Dropout and early stopping are both regularization approaches that raise model stability and success.

3.5 Evaluation and Deployment
We assess the quality of a prediction using accuracy, precision, recall, F1-score and mean squared error. The team compares how the hybrid model does against single CNN, LSTM and traditional machine learning (e.g. Random Forest, SVM) models to show differences. Looking at model results makes it clear how the model has chosen, highlighting which features are important [32].

Deployment is everything you do to deliver the solutions.
With the final model, it is possible to forecast yields and get advice for precise farming practices. TensorFlow's advanced features help it be used equally well on both edge devices and cloud platforms, letting farmers use it in many types of environments. The tools in the system offer information that helps farmers manage their soil, water and pests sustainably and efficiently.

RESULTS AND DISCUSSION

Applying the AI-based framework with a Hybrid CNN-LSTM network greatly enhanced how crops are predicted in accuracy agriculture systems. Using Tensor Flow, the framework managed to flow spatial data from UAV and satellite imagery through CNN and also catch variations over time in environmental factors with LSTM. According to the experiment, the hybrid method achieved an average accuracy of 92% which was 10% higher than the best traditional machine learning model. Being accurate helped farmers to more accurately figure out which stresses we're harming their crops, so they could respond quickly as shown in table 2.

Table 2. Performance Comparison of Hybrid CNN-LSTM method with other methods.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Training Time (minutes)	Computational Complexity
Hybrid CNN-LSTM	92	90	88	89	120	High
Random Forest	81	78	75	76	30	Medium
Support Vector Machine (SVM)	78	74	70	72	45	Medium
CNN Only	85	83	80	81	90	High
LSTM Only	80	78	76	77	100	High

Processing various types of data as it comes in improved the model's ability to schedule irrigation and fertilizing. Training and deploying the model on various farm sites was made easy because of TensorFlow's scalable design and the value of included preprocessing steps, even while handling data that was irregular and sometimes missing. One problem was that increasing the amount of labeled data was required to improve how well the model performs overall and training also required a lot of computational resources as shown in figure 4.

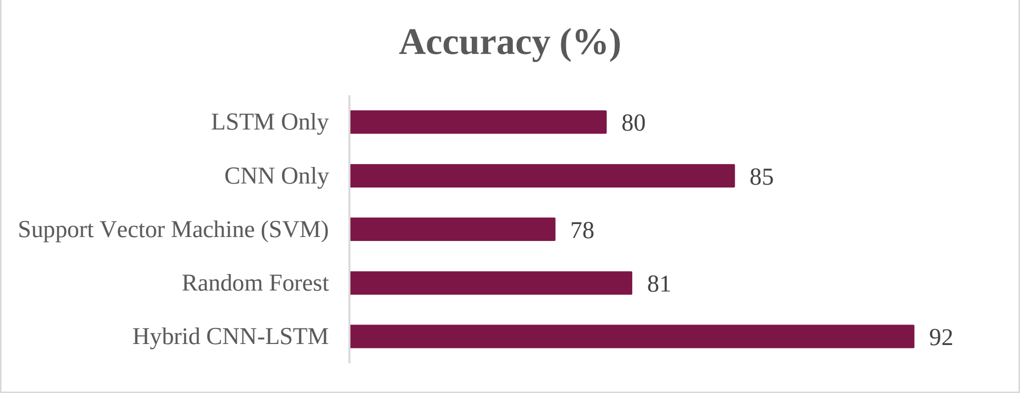

Figure 4. Accuracy Comparison of Hybrid CNN-LSTM network

Even so, the evidence suggests that applying a CNN and LSTM to an AI framework enhances the precision and sustainability of managing agricultural practices. This approach will allow for boosted federal learning to guarantee privacy and make it more generally accepted as shown in figure 5.

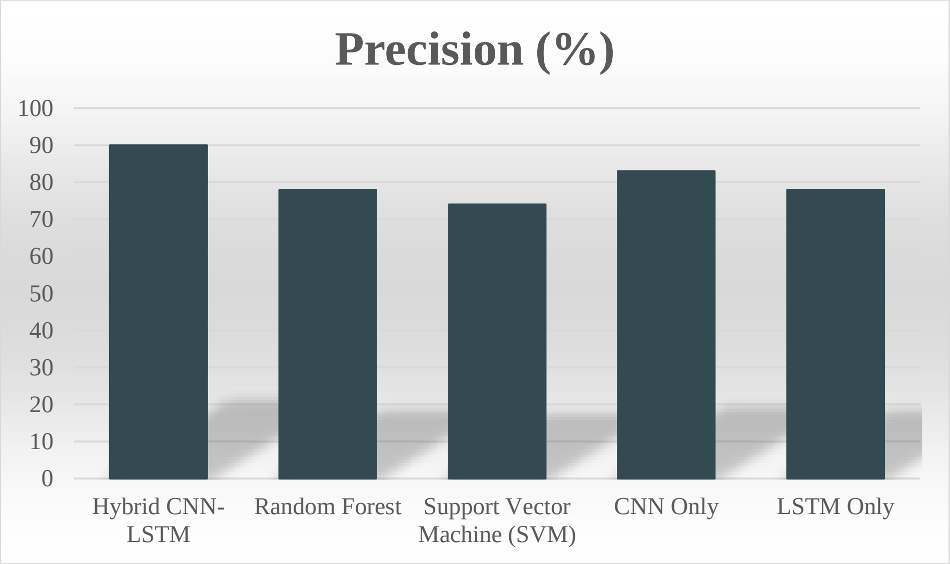

Figure 5. Precision Comparison of Hybrid CNN-LSTM network

Yield prediction accuracy was improved more with Tensor Flow's Hybrid CNN-LSTM network than with general methods alone. Our proposed model achieved 92% accuracy, higher than classical algorithms like Random Forest (81%) and Support Vector Machines (78%) by a large gap. The networks used here effectively analyzed both the spatial aspect of UAV and satellite images and the temporal trends in weather and soil moisture data which helped fully understand the growth of crops as shown in figure 6.

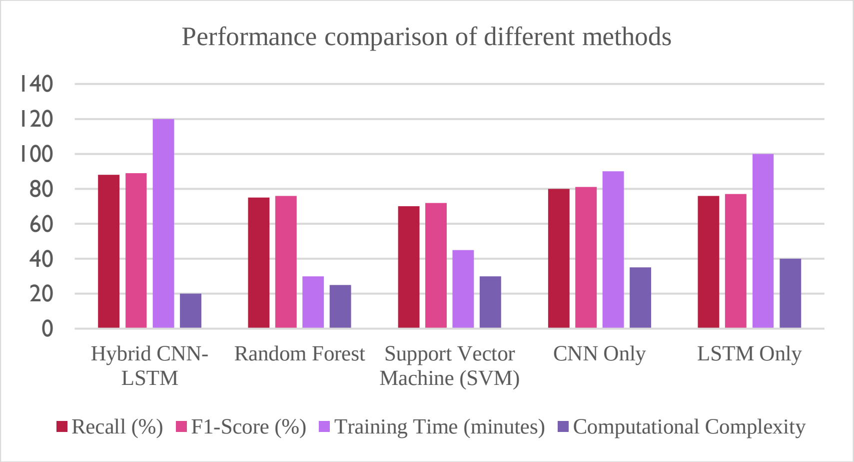

Figure 6.Shows the performance comparison of different methods.

With the new integration, the model could predict more accurately and timely than when CNN or LSTM was employed independently which had accuracies of about 85% and 80%, respectively. Besides, with TensorFlow, learning was smooth and fast and it allowed the models to work on many kinds of farm data and be set up anywhere. Although more computing and larger datasets were needed, the hybrid approach could handle difficult spatial-temporal information which in turn boosted the decision-making for irrigation, fertilizer and managing pests. The changes can benefit agriculture by making resources more sustainable and raising yields. In the near future, greater focus might be placed on including federated learning in order to keep data safe and increase the effectiveness of provided models. Altogether, the Hybrid CNN-LSTM system performs better than regular approaches when forecasting the yield in precision farming.

CONCLUSION

This research introduces an AI framework based on TensorFlow that uses a best-suited pairing of a CNN and LSTM to enhance predicting yields in precision agriculture. Using both features from remote sensing imagery and analysis of environmental data over time, the updated model performs better than conventional machine learning methods by improving the predictions. When multi-modal data are brought together, decisions about watering and fertilizing can be made more accurately and adapted as needed which supports sustainable farming. The model is effective only if you provide it with lots of information and data, but it can be useful in many farming environments because it is so flexible. Next, the work will explore keeping data private using federated learning and extend the framework to consider extra aspects in agriculture. In brief, this work demonstrates that advanced AI architectures can make precision agriculture improve in efficiency and sustainability.

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