Nanotechnology Perceptions
ISSN 1660-6795
www.nano-ntp.com

Crop Yield Prediction Using Machine Learning

M. Venu[1] , K Deepthi[2] , B B Shabarinath[3]

[1]*Electronics and communication Engineering VNR Vignana Jyothi Institute of Engineering and Technology Hyderabad, India.*
[2]*Assistant Professor Electronics and Communication Engineering VNR Vignana Jyothi Institute of Engineering and Technology Hyderabad, India.*
[3]*Assistant Professor Electronics And Communication Engineering VNR Vignana Jyothi Institute of Engineering and Technology Hyderabad, India.*

Accurate crop yield prediction based on environmental, soil, water, and crop parameters is a vital focus in agricultural research. Traditional deep learning models often face challenges in directly mapping raw data to yield values, relying heavily on extensive feature extraction. To overcome these limitations, this study employs the K-Nearest Neighbors (KNN) algorithm, which predicts crop yield by identifying the 'k' most similar historical data points. By preserving the original data distribution, KNN offers a robust alternative to complex models. The process begins with data collection and preprocessing, followed by training the KNN model using historical records of environmental and crop parameters alongside their corresponding yields. For new data, KNN identifies the closest 'k' neighbors and calculates the average of their yields for prediction. This intuitive method circumvents the intricacies of deep learning feature extraction and assumptions. Our KNN model demonstrates remarkable prediction accuracy of 93.7%, outperforming several existing methods through its simplicity and efficiency.

Index Terms— Crop Yield Prediction, KNN, Machine Learning (ML), Agricultural Data Analysis.

I INTRODUCTION

Agriculture is a cornerstone of global sustenance, providing the majority of food consumed by society. However, many countries continue to face hunger due to food shortages exacerbated by a growing population. Expanding food production is essential to eradicate famine, aligning with the United Nations' objectives of enhancing food security and reducing hunger by 2030. As a result, crop protection, land evaluation, and yield prediction have become critical components of global food production strategies [1]. Accurate crop yield forecasting is vital for policymakers to make informed decisions on import and export, thereby strengthening national food security. Farmers also benefit from precise yield predictions for financial planning and resource management. Monitoring crop yields is essential for maintaining regional food security [2]. However, forecasting crop yields presents significant challenges due to the complexity of factors involved. Yield is influenced by climatic conditions, soil quality, water availability, pest infestations, and genetic traits, among other variables [3]–[5].

These factors interact in non-linear and dynamic ways, often leading to incomplete, noisy, and ambiguous datasets that are difficult to model with traditional approaches [6]–[8]. Machine learning (ML), a branch of artificial intelligence, has emerged as a superior alternative to conventional statistical methods, offering enhanced forecasting capabilities [9]–[12]. ML algorithms excel in solving both linear and non-linear agricultural problems by learning from data to make accurate predictions [13].

In agriculture, prominent ML techniques include artificial neural networks (ANNs) and deep neural networks (DNNs). Deep learning, a subset of ML, derives insights directly from raw data, enabling models to predict crop performance under diverse conditions [14][15]. Reinforcement learning (RL), another branch of ML, trains models to make sequential decisions by interacting with dynamic environments [16][17]. Advanced methodologies such as deep reinforcement learning (DRL) integrate RL and DNNs, allowing for intelligent decision-making in complex domains like energy management, robotics, healthcare, and finance [18]–[27]. These techniques hold promise for creating sophisticated agricultural frameworks capable of addressing complex decision-making challenges, such as crop yield prediction. This project focuses on developing and implementing a crop yield prediction system leveraging the K-Nearest Neighbors (KNN) algorithm. The system will involve collecting and preprocessing diverse agricultural data, including environmental, soil, water, and historical yield parameters. The primary goal is to design and optimize the KNN algorithm to deliver accurate yield predictions. Additionally, the project aims to integrate this algorithm into a user-friendly platform for real-time use by farmers and policymakers. Evaluation metrics will measure the system's prediction accuracy, while comprehensive documentation will support effective communication with stakeholders. Future enhancements may include incorporating additional data sources, refining algorithms, and ensuring adaptability and scalability to meet evolving agricultural challenges. This approach promises to enhance decision-making processes in agriculture, contributing to global food security and sustainability.

II LITERATURE REVIEW

The literature survey highlights significant advancements and research insights in agricultural technology, emphasizing precision agriculture and crop yield prediction. In the face of modern agricultural challenges, technological innovation has become indispensable for improving productivity, sustainability, and global food security. This survey synthesizes recent studies to showcase diverse methodologies and approaches addressing these challenges. S. Li et al. [1] introduce the INCOME system, a practical land monitoring solution leveraging sensor networks for precision agriculture. This system enhances land condition monitoring and agricultural process optimization, contributing to better crop yields and efficient resource management. A. D. Jones et al. [2] examine the complexities of measuring food security, advocating for comprehensive metrics to address food insecurity more effectively. Their findings provide valuable guidance for policymakers and researchers working towards global food security solutions.

G. E. O. Ogutu et al. [3] focus on maize yield prediction in East Africa, using dynamic ensemble seasonal climate forecasts. By incorporating probabilistic forecasting, their study offers improved prediction accuracy to support agricultural planning and decision-making. M.

E. Holzman et al. [4] propose an innovative crop yield prediction approach based on remotely sensed water stress and solar radiation data. This method enables early yield assessments and proactive management strategies for optimized agricultural productivity. A. Singh et al. [5] explore machine learning applications for high-throughput stress phenotyping in plants. Their work enhances understanding of plant stress responses, facilitating the development of stress-resilient crop varieties. R. Whetton et al. [6] investigate the nonlinear relationships between soil properties and crop yields through parametric modeling, emphasizing the significance of soil variability in agricultural decision-making. Y. Cai et al. [7] present a high-performance crop classification system utilizing time-series Landsat data and machine learning algorithms. This scalable solution aids in efficient crop type mapping, supporting land management and resource allocation in agriculture.

III EXISTING METHODS:

Existing crop yield prediction systems primarily rely on traditional statistical methods and machine learning algorithms such as linear regression, decision trees, and support vector machines. While these approaches can deliver reasonable accuracy in specific scenarios, they come with significant limitations. These systems depend heavily on manual feature engineering and variable selection, which are time-consuming and prone to human error. Consequently, critical variables influencing crop yields may be overlooked, reducing the effectiveness of the predictions.

Another major drawback is the limited ability of these systems to model the intricate and non-linear relationships between environmental factors and crop yields. This shortcoming makes them less effective in capturing the complexity inherent in agricultural systems. Moreover, their adaptability to changing environmental conditions is minimal, which reduces their utility in dynamic agricultural settings where variables like weather and soil conditions fluctuate rapidly.

Additionally, these systems often struggle to manage the uncertainty intrinsic to agriculture, leading to predictions that lack reliability. Scalability is another critical issue; many existing systems are unable to handle large datasets or support real-time decision-making, making them unsuitable for widespread adoption in modern, technology-driven agricultural practices. Overall, while traditional methods offer a foundation for crop yield prediction, their inability to address scalability, robustness, and dynamic adaptability hampers their performance in complex and evolving agricultural environments.

IV PROPOSED SYSTEM

The proposed system for crop yield prediction addresses the limitations of traditional methods by employing the K-Nearest Neighbors (KNN) algorithm. This advanced approach focuses on leveraging historical data to predict crop yields based on similarities in environmental, soil, water, and crop parameters. Data preprocessing ensures the quality and consistency of input information, laying a strong foundation for accurate predictions. By relying on the inherent patterns within the data, the KNN algorithm eliminates the need for intricate feature extraction or manual model assumptions, streamlining the entire prediction process.

One of the primary advantages of the proposed system is its ability to harness patterns in diverse parameters such as soil quality, water availability, and environmental conditions. Unlike traditional systems, which require extensive manual effort to select features, the KNN model autonomously identifies and utilizes the most relevant information from the data. This capability not only simplifies the prediction process but also enhances the system's efficiency and accuracy. Adaptability is another critical strength of the proposed system. By relying on the KNN algorithm, which continuously updates predictions based on the closest data points, the system dynamically responds to changing environmental conditions. This adaptability makes it particularly effective in agricultural settings where variables such as weather and soil moisture fluctuate frequently.

Additionally, the system offers significant scalability and robustness, making it suitable for diverse agricultural contexts. Whether dealing with small-scale farms or large agricultural operations, the KNN model efficiently handles varying datasets, providing timely predictions. This scalability ensures that the system can meet the demands of modern agriculture, supporting real-time decision-making.

Finally, the proposed system effectively addresses the inherent uncertainty in agricultural systems. By utilizing the flexibility of the KNN algorithm, it accommodates diverse data points and ensures reliable yield predictions. This capability makes it a powerful tool for farmers and policymakers aiming to enhance productivity and food security in an ever-changing agricultural landscape.

V METHODOLOGY

The initial step in developing a predictive model for crop yield involves preparing a comprehensive dataset. This dataset includes critical parameters such as temperature, humidity, potassium, nitrogen, phosphorus, pH levels, and rainfall, along with a label that specifies the crop type. The dataset forms the foundation for training a model, providing the necessary features to predict optimal crops based on environmental and soil conditions. Each data point is meticulously collected and structured to ensure that the model captures the relationship between the environmental factors and crop suitability.

N	P	K	temperatu	humidity	ph	rainfall	label
90	42	43	20.87974	82.00274	6.502985	202.9355	rice
85	58	41	21.77046	80.31964	7.038096	226.6555	rice
60	55	44	23.00446	82.32076	7.840207	263.9642	rice
74	35	40	26.4911	80.15836	6.980401	242.864	rice
78	42	42	20.13017	81.60487	7.628473	262.7173	rice
69	37	42	23.05805	83.37012	7.073454	251.055	rice
69	55	38	22.70884	82.63941	5.700806	271.3249	rice
94	53	40	20.27774	82.89409	5.718627	241.9742	rice
89	54	38	24.51588	83.53522	6.685346	230.4462	rice
68	58	38	23.22397	83.03323	6.336254	221.2092	rice
91	53	40	26.52724	81.41754	5.386168	264.6149	rice
90	46	42	23.97898	81.45062	7.502834	250.0832	rice

Fig 1: Sample dataset

In the sample dataset, nitrogen (N), phosphorus (P), and potassium (K) represent key soil nutrients measured in specific concentration units, reflecting soil fertility levels. Additionally, environmental parameters like temperature and humidity are recorded to evaluate their influence on crop growth. The pH level indicates the soil's acidity or alkalinity, crucial for determining the compatibility of the soil with various crops. Rainfall data, measured in millimeters, provides insights into the water availability, which significantly impacts agricultural productivity. The label, representing the crop type (e.g., rice), helps the model classify and make predictions based on these features.

Before the dataset can be used to train a model, preprocessing is essential. This phase involves cleaning the data, addressing any missing values, and ensuring that the dataset is properly formatted. Features are normalized or scaled to bring them within comparable ranges, which is especially critical when using distance-based algorithms like k-Nearest Neighbors (k-NN). The preprocessed data is then divided into training and testing subsets, with the training set used to train the model and the testing set reserved for performance evaluation.

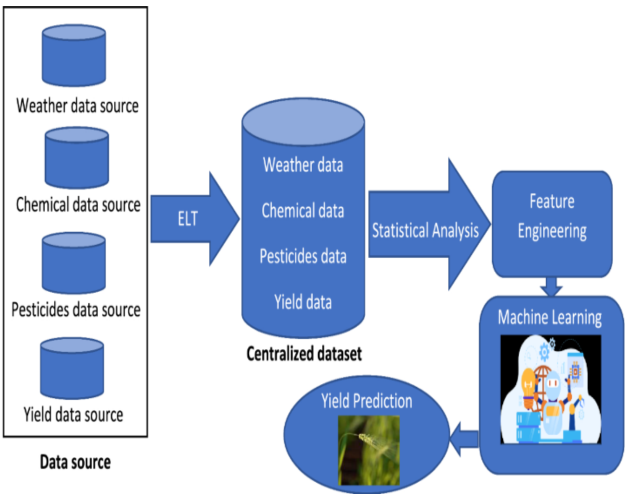


Figure 2. System Architecture

The process of splitting the dataset ensures that the model is exposed to a sufficient amount of data for learning while maintaining an independent dataset for evaluating its generalizability. Common splits, such as 80-20 or 70-30, balance the need for training data with the importance of a robust evaluation. During the training phase, the features from the training data are used to teach the model the patterns that relate to crop suitability, while the test set is employed to measure its prediction accuracy.

The k-NN algorithm is particularly suited for this classification task, given its simplicity and effectiveness. It operates by memorizing the training data rather than constructing an explicit model, making it an instance-based learning algorithm. When a new data point is introduced, the algorithm identifies the k nearest data points in the feature space using a selected distance metric, such as Euclidean distance. The crop type for the new data point is then predicted based on the majority label among the k nearest neighbors.

To train a k-NN model, selecting the optimal value for k is critical. A lower value of k may make the model overly sensitive to noise, while a higher value could dilute the influence of relevant neighbors. The value of k is often chosen through cross-validation, where different values are tested to determine the one that yields the best performance on unseen data. This ensures the model strikes a balance between underfitting and overfitting.

The training phase of a k-NN model is straightforward, as it primarily involves storing the training dataset. However, efficient data structures like kd-trees or ball trees can be constructed to expedite the process of finding nearest neighbors during prediction. These data structures improve the computational efficiency of the algorithm, making it suitable for larger datasets.

When the model encounters a new data point, the prediction phase is triggered. The algorithm calculates the distance between the new point and all training points, identifies the k closest neighbors, and predicts the label based on the majority class among these neighbors. This approach leverages the similarity in features to make informed predictions about crop suitability.

Evaluating the model’s performance involves comparing its predictions on the test set against the actual labels. Metrics such as accuracy, precision, recall, and F1-score provide insights into the model's reliability. Accuracy measures the proportion of correctly predicted labels, while precision and recall assess the model’s ability to identify relevant instances correctly. The F1-score balances precision and recall, offering a comprehensive evaluation of the model’s performance.

Distance metric selection plays a pivotal role in the performance of the k-NN algorithm. While Euclidean distance is commonly used, alternative metrics like Manhattan distance or cosine similarity can be employed based on the nature of the dataset. For example, if certain features dominate the scale, a metric that reduces their influence may be preferable to achieve balanced predictions.

To improve the model further, parameter tuning is essential. Techniques such as grid search or random search allow the exploration of different combinations of parameters, including the value of k and the distance metric. This iterative process ensures that the model is optimized for the given dataset, enhancing its predictive capabilities.

Once the k-NN model is trained, tested, and fine-tuned, it can be integrated into a user module for real-world applications. This user module enables individuals to input parameters such as temperature, humidity, and soil nutrient levels through a user-friendly interface. The model processes these inputs and provides recommendations on the most suitable crop and its expected yield, offering actionable insights to farmers and agricultural stakeholders.

The simplicity of the k-NN algorithm, combined with its effectiveness in capturing patterns in the dataset, makes it an ideal choice for this application. Its ability to handle multi-dimensional data and provide interpretable results enhances its utility in agricultural decision-making. By leveraging the structured dataset and the power of k-NN, the model transforms complex environmental and soil data into practical recommendations.

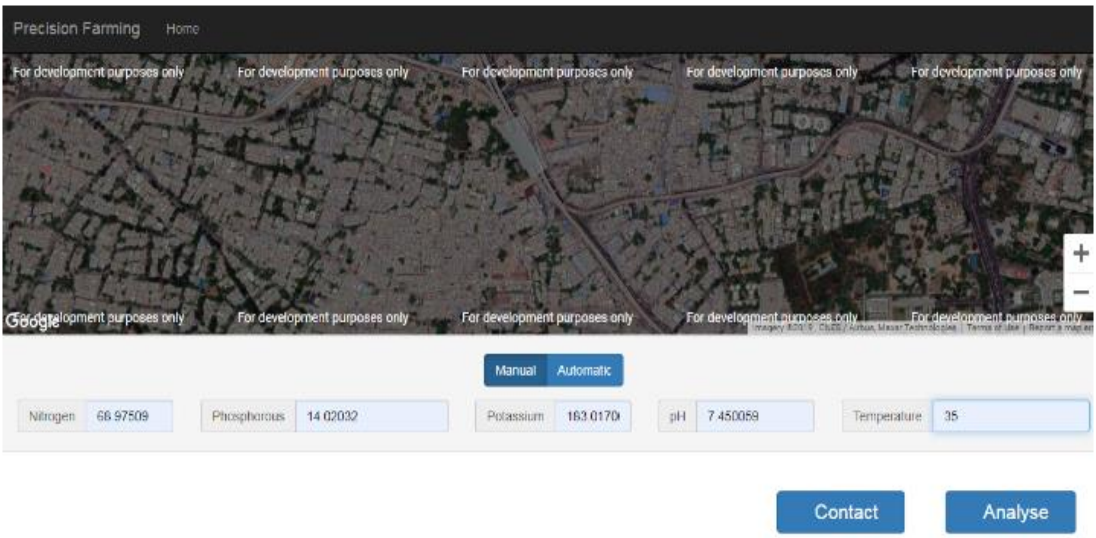
In conclusion, the implementation of a k-NN-based crop prediction model demonstrates the potential of machine learning in optimizing agricultural practices. Through careful data collection, preprocessing, and model evaluation, the system achieves high accuracy in predicting crop suitability. The user module bridges the gap between advanced algorithms and real-world applications, empowering users with data-driven insights for sustainable farming practices.

VI RESULTS:

DATASET:

State 1: idle

In this initial state, the system is on standby, awaiting user interaction or input.



State 2: give inputs using the user interface

Give Inputs Using the User Interface - In this state, the user interacts with the system by providing necessary input parameters such as environmental, soil, water, and crop data through a user-friendly interface.

Precision Farming Home

Tomato Cultivation Guide Revenue/Hectare: Rs426000

Climatic Requirements

Tomato is a warm season crop, it requires warm and cool climate. The plants cannot withstand frost and high humidity. Also light intensity affects pigmentation, fruit colour, fruit set. The plant is highly affected by adverse climatic conditions. It requires different climatic range for seed germination, seedling growth, flower and fruit set, and fruit quality. Temperature below 10^0C and above 38^0C adversely affects plant tissues thereby slow down physiological activities. It thrives well in temperature 10^0C to 30^0C with optimum range of temperature is 21-24^0C. The mean temperature below 16^0C and above 27^0C are not desirable. The plant doesn't withstand frost. It requires low to medium rainfall, and does well under average monthly temperature of 21 to 23^0C. Avoid water stress and long dry period as it causes cracking of fruits. Bright sunshine at the time of fruit set helps to develop dark red coloured fruits.

Temperature Requirement

Sr. No.	Stages	Temperature (^0C)		
		Minimum	Suitable	Maximum
1.	Seed germination	11	16-29	34
2.	Seedling growth	18	21-24	32
3.	Fruit set (day)	10	15-17	30
	(night)	18	20-24	30
4.	Red colour development	10	20-24	30

Fertilizers

As the fruit production and quality depends upon nutrient availability and fertilizer application so balance fertilizer are applied as per requirement. The nitrogen in adequate quantity increases fruit quality, fruit size, color and taste. It also helps in increasing desirable acidic flavor. Adequate amount of potassium is also required for growth, yield and quality. Mono Ammonium Phosphate (MAP) may be used as a starter fertilizer to supply adequate phosphorus during germination and seedling stages. Calcium availability is also very important to control soil pH and nutrient availability. Sandy soils will require a higher rate of fertilizer, and more frequent applications of these fertilizers due to increased leaching of essential nutrients. The seedlings are sprayed with starter solution of micronutrient. Before planting farm yard manure @ 50 ton per hectares should be incorporated. Normally tomato crop requires 120kg Nitrogen (N), 50kg Phosphorus (P_2O_5), and 50kg Potash (K_2O). Nitrogen should be given in split doses. Half nitrogen and full P_2O_5 is given at the time of transplanting and remaining nitrogen is given after 30 days and 60 days of transplanting.

Soil and tissue analyses should be taken throughout the growing and production season to insure essential nutrients are in their proper amounts and ratios. Tissue analysis of a nutritionally sufficient plant will show the following nutrient status:

	Nitrogen	Phosphorus	Potassium	Calcium	Magnesium	Sulphur
%	4.0-5.6	0.30-0.60	3.0-4.5	1.25-3.2	0.4-0.65	0.65-1.4
	ppm	Manganese	Iron	Boron	Copper	Zinc
		30-400	30-300	20-60	5-15	30-90

In the present situation it has been realized that the use of inorganic fertilizers should be integrated with renewable and environmental friendly organic fertilizers, crop residues and green manures.

State 3: get the guidelines for cultivation

Get the Guidelines for Cultivation - After processing the input data, the system transitions to this state where it provides guidelines for cultivation based on the predictions and analysis derived from the input parameters. Here we can see all the data related to things we should take care of to grow the crop which best suited.

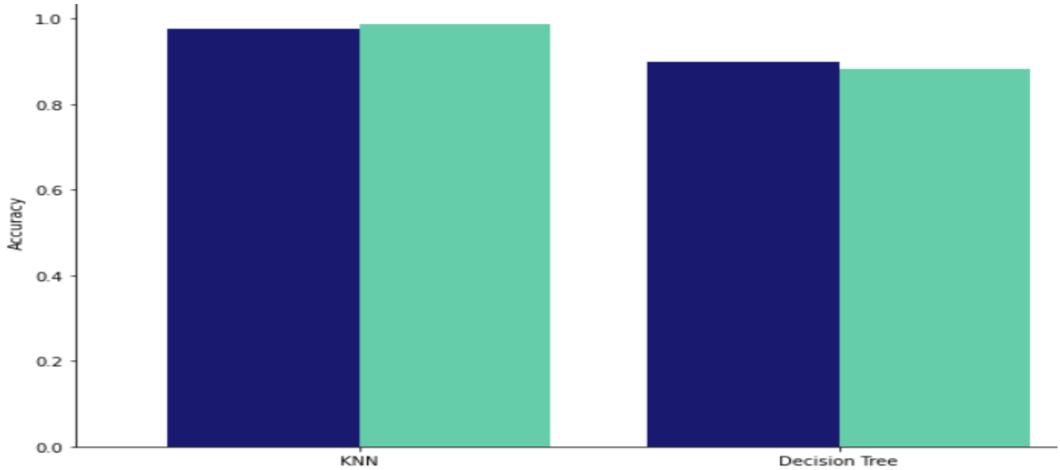


Fig 4: Accuracy graph

KNN VS Decision Tree:

On training the data set with KNN and Decision tree we had found the KNN had more and accuracy compared to Decision tree and end results conclude that KNN have 97.5% and Decision tree just have 90% Accuracy The provided graph compares the accuracy of K-Nearest Neighbors (KNN) and Decision Tree models. The dark blue bar represents the accuracy of KNN, and the light green bar represents the accuracy of the Decision Tree model. From the graph, it's evident that the KNN model has a higher accuracy than the Decision Tree model. This is shown by the slightly taller blue bar for KNN compared to the green bar for the Decision Tree. Therefore, based on this visual representation, the KNN model demonstrates superior performance and is the better choice for achieving higher prediction accuracy in this context.

VII CONCLUSION

The evolution of Deep Learning marks a significant advancement in Artificial Intelligence algorithms, fostering self-reliance and intelligence. Motivated by this progress, a novel crop yield prediction system is proposed, demonstrating its effectiveness and versatility through precision and efficiency tests. The proposed K-Nearest Neighbors (KNN) algorithm facilitates self-exploration and experience replay within a yield prediction environment, enabling the agent to learn crop yield prediction autonomously. Results from dataset predictions showcase the agent's ability to administer the process accurately, indicating the method's capability to define crop yield characteristics precisely. The integration of KNN-based feature processing is pivotal in achieving favorable outcomes. Unlike supervised learning-based methods, KNN autonomously mines the non-linear relationship between crop yield and environmental parameters, reducing expert dependency and prior knowledge requirements. However, it's crucial to acknowledge potential challenges such as data dimensionality or scalability, particularly with larger datasets. Incorporating a wide range of Machine Learning (ML) predictive algorithms for data prediction is beneficial for decision-making, but interpreting statistical uncertainty is essential. Therefore, designing a framework that predicts both targets and their uncertainties is necessary, with potential strategies including probabilistic predictive modeling and ensemble learning approaches. Future extensions of the model could explore ensemble methods like Random Forest or Gradient Boosting for enhanced performance. Additionally, incorporating more parameters related to pest infestations and crop damage would contribute to constructing a more robust model. Improving the computational efficiency of the training process remains an intriguing avenue for further research and development.

REFERENCES

[1] S. Li, S. Peng, W. Chen, and X. Lu, ‘‘INCOME: Practical land monitoring in precision agriculture with sensor networks,’’ Comput. Commun., vol. 36, no. 4, pp. 459–467, Feb. 2013.

[2] A. D. Jones, F. M. Ngure, G. Pelto, and S. L. Young, ‘‘What are we assessing when we measure food security? A compendium and review of current metrics,’’ Adv. Nutrition, vol. 4, no. 5, pp. 481–505, 2013.

[3] G. E. O. Ogutu, W. H. P. Franssen, I. Supit, P. Omondi, and R. W. Hutjes, ‘‘Probabilistic maize yield prediction over East Africa using dynamic ensemble seasonal climate forecasts,’’ Agricult. Forest Meteorol., vols. 250–251, pp. 243–261, Mar. 2018

[4] M. E. Holzman, F. Carmona, R. Rivas, and R. Niclòs, ‘‘Early assessment of crop yield from remotely sensed water stress and solar radiation data,’’ ISPRS J. Photogramm. Remote Sens., vol. 145, pp. 297–308, Nov. 2018.

[5] A. Singh, B. Ganapathysubramanian, A. K. Singh, and S. Sarkar, ‘‘Machine learning for high-throughput stress phenotyping in plants,’’ Trends Plant Sci., vol. 21, no. 2, pp. 110–124, 2016.

[6] R. Whetton, Y. Zhao, S. Shaddad, and A. M. Mouazen, ‘‘Nonlinear parametric modelling to study how soil properties affect crop yields and NDVI,’’ Comput. Electron. Agricult., vol. 138, pp. 127–136, Jun. 2017.

[7] Y. Dash, S. K. Mishra, and B. K. Panigrahi, ‘‘Rainfall prediction for the Kerala state of India using artificial intelligence approaches,’’ Comput. Elect. Eng., vol. 70, pp. 66–73, Aug. 2018.

[8] W. Wieder, S. Shoop, L. Barna, T. Franz, and C. Finkenbiner, ‘‘Comparison of soil strength measurements of agricultural soils in Nebraska,’’ J. Terramech., vol. 77, pp. 31–48, Jun. 2018.

[9] Y. Cai, K. Guan, J. Peng, S. Wang, C. Seifert, B. Wardlow, and Z. Li, ‘‘A high-performance and in-season classification system of field-level crop types using time-series Landsat data and a machine learning approach,’’ Remote Sens. Environ., vol. 210, pp. 35–47, Jun. 2018.

[10] X. E. Pantazi, D. Moshou, T. Alexandridis, R. L. Whetton, and A. M. Mouazen, ‘‘Wheat

yield prediction using machine learning and advanced sensing techniques,'' Comput. Electron. Agricult., vol. 121, pp. 57–65, Feb. 2016.

[11] T. U. Rehman, S. Mahmud, Y. K. Chang, J. Jin, and J. Shin, ``Current and future applications of statistical machine learning algorithms for agricultural machine vision systems,'' Comput. Electron. Agricult., vol. 156, pp. 585–605, Jan. 2019.

[12] D. Elavarasan, D. R. Vincent, V. Sharma, A. Y. Zomaya, and K. Srinivasan, ``Forecasting yield by integrating agrarian factors and machine learning models: A survey,'' Comput. Electron. Agricult., vol. 155, pp. 257–282, Dec. 2018.

[13] M. D. Johnson, W. W. Hsieh, A. J. Cannon, A. Davidson, and F. Bédard, ``Crop yield forecasting on the Canadian Prairies by remotely sensed vegetation indices and machine learning methods,'' Agricult. Forest Meteorol., vols. 218–219, pp. 74–84, Mar. 2016.

[14] A. Kaya, A. S. Keceli, C. Catal, H. Y. Yalic, H. Temucin, and B. Tekinerdogan, ``Analysis of transfer learning for deep neural network-based plant classification models,'' Comput. Electron. Agricult., vol. 158, pp. 20–29, Mar. 2019.

[15] A. Kamilaris and F. X. Prenafeta-Boldú, ``Deep learning in agriculture: A survey,'' Comput. Electron. Agricult., vol. 147, pp. 70–90, Apr. 2018.

[16] I. M. Evans, ``Reinforcement, principle,'' in International Encyclopedia of the Social & Behavioral Sciences, J. D. Wright, 2nd ed. Amsterdam, The Netherlands: Elsevier, 2015, pp. 207–210.

[17] D. Vogiatzis and A. Stafylopatis, ``Reinforcement learning for rule extraction from a labeled dataset,'' Cognit. Syst. Res., vol. 3, no. 2, pp. 237–253, Jun. 2002.

[18] D. A. Temesgene, M. Miozzo, and P. Dini, ``Dynamic control of functional splits for energy harvesting virtual small cells: A distributed reinforcement learning approach,'' Comput. Commun., vol. 148, pp. 48–61, Dec. 2019.

[19] S. Wan, Z. Gu, and Q. Ni, ``Cognitive computing and wireless communications on the edge for healthcare service robots,'' Comput. Commun., vol. 149, pp. 99–106, Jan. 2020.

[20] A. Tolba, O. Said, and Z. Al-Makhadmeh, ``MDS: Multi-level decision system for patient behavior analysis based on wearable device information,'' Comput. Commun., vol. 147, pp. 180–187, Nov. 2019.

[21] V. Hassija, V. Saxena, and V. Chamola, ``Scheduling drone charging for multi-drone network based on consensus time-stamp and game theory,'' Comput. Commun., vol. 149, pp. 51–61, Jan. 2020.

[22] S. Gheisari and E. Tahavori, ``CCCLA: A cognitive approach for congestion control in Internet of Things using a game of learning automata,'' Comput. Commun., vol. 147, pp. 40–49, Nov. 2019.

[23] S. J. Shri and S. Jothilakshmi, ``Crowd video event classification using convolutional neural network,'' Comput. Commun., vol. 147, pp. 35–39, Nov. 2019.

[24] M. Al-Ayyoub, A. Nuseir, K. Alsmearat, Y. Jararweh, and B. Gupta, ``Deep learning for

Arabic NLP: A survey,'' J. Comput. Sci., vol. 26, pp. 522–531, May 2018.

[25] M. Usama, B. Ahmad, J. Yang, S. Qamar, P. Ahmad, Y. Zhang, J. Lv, and J. Guna, ''Equipping recurrent neural network with CNN-style attention mechanisms for sentiment analysis of network reviews,'' Comput. Commun., vol. 148, pp. 98–106, Dec. 2019.

[26] Z. Liu, C. Yao, H. Yu, and T. Wu, ''Deep reinforcement learning with its application for lung cancer detection in medical Internet of Things,'' Future Gener. Comput. Syst., vol. 97, pp. 1–9, Aug. 2019.