Advances in Consumer Research
ISSN (Print): 0098-9258
ISSN(Online): 3079-1766

Vol. 2, Issue 2 (2025) https://acr-journal.com/

Survey on Crop yield prediction using machine learning algorithm

Dr.Supriya Nandikolla[1], Prof.Bhuvan Unhelkar[2], Prof.Pravin R Kshirsagar[3], Prof.Prasun Chakrabarti[4], Dr.Shrikant V. Sonekar[5]

[1]Post-Doctoral Fellowship Research Scholar, Department of Information Systems and Decision Sciences, University of South Florida, USA.

[1]Associate Professor, Department of CSE (Data Science), School of Engineering, Malla Reddy University Hyderabad, Telangana.

Email ID: nsupriyacse@gmail.com

[2]Professor of Information Systems and Decision Sciences, Muma College of Business, University of South Florida, Sarasota, Florida, USA.

Email ID: bunhelkar@usf.edu

[3]Professor, Electronics & Telecommunications Engineering, J D College of Engineering & Management, Nagpur, INDIA. Email ID: pravinrk88@yahoo.com

[4]Professor, Department of Computer Science and Engineering, Sir Padampat Singhania University, Udaipur, Rajasthan, India.

Email ID: drprasun.cse@gmail.com

[5]Principal & Professor, Department of Computer Science & Engineering, J D College of Engineering & Management, Nagpur,India.

Email ID: principal@jdcoem.ac.in

Cite this paper as: Dr.Supriya Nandikolla, Prof.Bhuvan Unhelkar, Prof.Pravin R Kshirsagar, Prof.Prasun Chakrabarti, Dr.Shrikant V. Sonekar, (2025) Survey on Crop yield prediction using machine learning algorithm. *Advances in Consumer Research*, 2 (2), 805-812.

KEYWORDS

Machine Learning, Sustainable agriculture, pre-processing, feature engineering.

ABSTRACT

The agricultural sector remains essential to preserve worldwide food security together with economic stability especially in territories where farmers heavily depend on agriculture for financial stability. The necessity to predict crop yields accurately increases because of population growth combined with changing environmental conditions. The research paper provides an organized review of crop yield forecasting systems which implement machine learning algorithms. The research evaluates supervised and ensemble learning models such as Random Forest (RF), Support Vector Machine (SVM) and Gradient Boosting (GB) and Artificial Neural Networks(ANNs) as well as advanced Deep Learning (DL) approaches to solve agricultural system complexities. The analysis shows that innovative ML algorithms need development for diverse high-dimensional data sets which include weather patterns and soil characteristics and crop types and historical yield records. This research analyzes recent advancements of remote sensing systems and IoT-based data collection regarding their functions for live accurate prediction operations. This research highlights the necessity of feature engineering together with data preprocessing alongside hybrid modeling strategies for solving issues that affect datasets and environmental factors as well as scalability. Different algorithms perform effectively for yield prediction purposes because their analysis has demonstrated high accuracy and robust prediction capabilities. The research provides detailed information to assist both practitioners and researchers who want to improve decision systems in agriculture with sustainable machine learning approaches for crop management.

1. INTRODUCTION

Different machine learning (ML) approaches support operations across various fields which involve consumer behavior prediction both in stores and mobile phone usage prediction. People have implemented machine learning systems for agricultural purposes for multiple years. Precision agriculture represents a complex issue when predicting crop yields and several successful models have been tested throughout time. Multiple datasets must be used for crop yield prediction as the output relies on various influencing factors such as weather patterns and soil quality and seed variety and fertilizer use patterns. The process of crop yield prediction requires multiple complex stages because it is not an easy matter to predict. Modern crop yield prediction tools create reasonable estimations of actual yield outputs but additional improvement in yield prediction accuracy would be beneficial.

Machine learning within artificial intelligence through its focus on learning methods for developing practical yield prediction models based on multiple features. The method of machine learning enables users to detect patterns as well as discover hidden relationships and hidden insights from raw data collections. Training models requires datasets containing past experiences which serve as the basis for outcome representation. A predictive model requires several features during its construction phase while the parameters are determined with historical data from training. An unutilized part of historical data serves as the performance evaluation tool after completion of the testing phase.

A systematic investigation of research papers about ML applications in crop yield prediction has been conducted to understand existing work. The survey highlights possible research deficits within specific problem domains for practitioners and researchers who need to perform new studies on those subject areas. The systematic literature review methodology enables researchers to access relevant studies from electronic databases and synthesize those findings for answering the research questions previously established in the study. The final results of an SLR study produce new ways of thinking that assist upcoming researchers in mastering existing developments.

Diepeveen and Armstrong in [2] examine crop-related data distribution to farmers for better yield and profit enhancement decisions. The information benefits one crop type yet remains unsuitable for others since it functions in generalized fashion. Data mining applications help process agricultural data to enhance the integrity and validity levels for multiple farming conditions. A major obstacle lies in detecting those characteristics which impact crop yield particularly geographic location, soil type, seasonal conditions, nutrition and grain yield and quality, sowing and harvest data alongside environmental stress tolerance. The research implemented data mining approaches to assist growers in finding optimal trait combinations for their search for superior performing species. Various methods operated across each geographical region.

The study presented in [1] by Murynin et al. examines the correlation between forecast accuracy and its predictive outcomes. The linear model stands as the starting point when predicting yield. The prediction model receives non-linear attributes extension which enhances its ability to predict accurately. The modifications include predictions based on sustained technology advancements for agricultural productivity together with yield level variations across regions. The model accuracy estimation utilizes a period between predictive formation time and harvest time.

The research of Tseng [3] employed IoT equipment for smart farming to detect crop output forecasting. Weather factors have traditionally damaged agricultural crops and current intelligent agricultural models leverage big data analysis systems to estimate farm crop yields. The IoT sensor-based monitoring system checked all areas of a farming field through its ability to detect both atmospheric pressure and humidity and moisture content and temperature and soil salinity. The primary goal of big data analysis within IoT systems involved studying crop cultivation practices employed by farmers and environmental anomalies. A benefit from using the developed model was the 3D cluster analysis method which evaluated environmental relationships while also assessing the farmer methodological recommendations. The implemented model behaved unpredictably after exposure to probable risks in the parameters of soil moisture and temperature along with air humidity.

The research of Tiwari and Shukla [4] created a crop yield predicting model through the integration of CNN technology with Geographical Index. The current model encountered difficulties because agricultural drifts used for crop cultivation experienced continuous failures despite being incompatible with environmental elements such as temperature and weather conditions and soil state. The developed CNN model took spatial features as entry data but BPNN trained it for error detection. Real-time testing of the developed model involved authentic geospatial resources to generate its dataset. The developed model achieved lower relative error but it resulted in a decrease of predictive efficiency for crop yields.

The Robust Deep-Learning method which Fuentes et al., [5] used helped identify pests and tomato plant infections in crops. The predictive model encountered difficulties with yield prediction because pests and diseases in crops generated major financial losses. The developed model relies on deep meta architectural prediction of pests affecting plants. The developed model incorporates three indicator features using deep metaarchitecture by combining Single Shot Multibox Detector (SDD) and Faster region-based CNN as well as Region-Based Fully CNN. A method for global and local period explanations was proposed through the execution of the deep meta-architecture and feature extractors. The increasing data volume leads to system precision and lowers both training-related false positives. The developed model demonstrated success in identifying different pests together with diseases though performing complex analyses of situations within nearby areas. The robust deep learning method takes longer time and high computational costs because of its complex pre-processing techniques.

The yield prediction of soybeans was conducted through Deep CNN-LSTM methodology by Sun et al. [6]. Prior yield prediction became a fundamental influence that improved the practice of yield mapping while enhancing harvest management and crop insurance operations and crop market planning and remote sensing capabilities. A practical and feasible version of the CNN-LSTM approach underwent verification testing for predicting PM2.5 concentration levels in the developed model. The DNN structure included CNN alongside LSTM through the analysis of historical data components like cumulated wind speed and duration of rain as well as PM 2.5 concentration levels. The authors utilized histogram-based tensor alteration to merge remote sensing data because linking various data sources with different resolutions presented difficulties but Bondre and Mahagonkar [7] resolved this challenge through the application of ML techniques for crop yield and manure recommendation prediction. Crop yield prediction in farming required significant resolution until researchers created a machine learning system to address this problem. The evaluation of the developed model focused on its ability to estimate agricultural crop production. A key benefit of the developed model used past agricultural data to predict crops while generating fertilizer suggestions for each agricultural product through random forest and SVM method applications. The implementation of a smart irrigation system to improve farm yield did not take place.

Developing annual yield prediction models for major crops is achieved through data mining methods utilized by Devika and Ananthi [8]. The developed data mining method allowed farmers to harvest their yield despite lacking water resources and unpredictable weather conditions. The model gathered agricultural documentation which used to be stored and processed to produce evaluations of valuable crop yields. Some data mining operations acquire training data from already analyzed past reports before applying these documents to the exploitation phase. The developed model achieved the best prediction rates for the yield of sugarcane and cotton and turmeric crops. The model showed limited accuracy for wheat alongside rice and other farming products.

Soil review estimation of mustard crop yield employed ML technology according to Pandith et al. [9]. The development of ML technology solved the issue of soil impacts on agriculture crop yield estimation. The prediction system for mustard crop yield analysis based on soil studies employed four ML methods consisting of multinomial logistic regression, K-nearest neighbor (KNN), ANN, random forest and Naive Bayes. The anticipated yield predictions from the developed model could function with the presence of fertilizer as an input for supporting both soil diagnostic procedures and agricultural decision making while dealing with low yield expectations. The predictive model proved difficult to use in large datasets because of its design to process extensive soil data within big data environments.

P.S. Maya Gopal together with R. Bhargavi [10] created a new method for CYP effectiveness that manipulated an ANN system. A model based on ANN and statistical methods as well as Multi Linear Regression (MLR) algorithms predicted the crop yield quantity. The model employed intrinsic behaviors in its integrated MLR-ANN approach for CYP analysis which studied the accuracy through MLR calculation of coefficients and ANNs evaluation of input layer weights and bias. The predictive model relied on Feed forward ANN with back propagation. This model performed yield forecasting. Khaki S. and Wang L have investigated the utility of DNN for CYP to produce accurate yield prediction models [11]. The model established basic understanding about how yield varies with interactive factors by using a versatile powerful calculation system. The applied regression trees proved more efficient in comparison to supervised models according to the resulting analysis. The main drawback of the study was its inability to discover advanced models that could present accurate outcomes.

The research by T. Vijayakumar [12] focused on Posed Inverse Problem Rectification through Developed Novel Deep CNN. The current approaches delivered impressive results while presenting difficulties including high computational expenses and constraints in picking forward operator parameters and adjoint operators along with forward operators parameters. The implemented model with CNN directly inverted to find solutions for solving the convolution inverse problem. The analytical model incorporated physical inversion methods before adopting multi-resolution decomposition with residual learning that caused artifacts to emerge. The model was not accepted because of high noise levels. T. Senthil Kumar created a marketing decision support system through data mining base approaches that combines hybrid ML techniques for solving financial and marketing industry problems. A decision support system performs decision-making activities to aid organizational performance analyses of actual operational conditions. The present models led the organization into greater market competition because of globalization privatization along with liberalization. The market competition runs equally while companies put into practice their planned marketing plans successfully. A required optimization model needed to be developed because the process became complex and evaluation results suffered during implementation.

2. OVERVIEW OF EXISTING APPROACHES

Traditional statistical along with machine learning techniques served the crop yield prediction field in the past but deep learning approaches became prominent because of their capability to handle complex non-linear relationships in agricultural data.

2.1 Survey on Deep Learning

Multiple deep learning approaches have been applied for crop yield prediction using different data elements that include satellite imagery together with weather data and soil characteristics and historical yield records. The standard group of deep learning models consists of:

The static regression method along with the mechanistic approach proves difficult to produce dependable crop yield prediction models because of their restricted application range and prediction uncertainties [13]. Multiple studies across research conducted predictive modeling for crop yields through regression tree, random forest, multivariate regression, association rule mining along with artificial neural networks [14]. Machine learning models perceive crop yield as an obscure function of their input variables including weather components along with soil conditions. Supervised learning methods within machine learning cannot detect nonlinearity patterns between the input and output data points. New technological developments during recent years enabled the creation of an improved crop yield prediction model that uses deep learning systems. Deep learning stands separate from traditional machine learning because it uses hierarchical structures to connect multiple layers and enables assessment of both untagged and unorganized data. The agricultural field extensively employs deep learning because this technology effectively examines enormous datasets while discovering associative relationships between numerous variables and employing nonlinear functions. These techniques serve to extract features from big datasets when working in an unsupervised environment. Feature extraction benefits more when deep learning approaches are applied compared to traditional machine learning approaches according to research in [15]. An accurate crop yield prediction depends on influencing factors of crop growth so deep learning effectively extracts information from existing data.

Each nonlinear layer within deep neural networks transforms untested input data into extracted information at that specific point. Deep neural networks using multiple hidden layers serve to determine the nonlinear relationships that exist between input and output variables. The training procedure remains challenging because new hardware solutions and optimization methods are required alongside their implementation. The number of hidden layers has strong potential for effectiveness yet requires specific implementation techniques to overcome its limitations. Deep neural networks experience reduced gradient vanishing through the implementation of residual skip connections for network operation. Deep learning methods achieve enhanced performance through the implementation of three optimizational techniques including stochastic gradient descent (SGD), batch normalization and dropout. The following list presents different deep learning techniques.

The analysis of structured and unstructured data proves to be an exceptional task for deep learning as a machine learning subfield [16]. The agricultural sector regularly adopts this technology because it assists in managing big datasets and detecting correlating variables and working with non-linear equations [17]. Deep learning outperforms traditional methods in feature extraction, crucial for agricultural yield prediction. The three main deep learning methods currently used for crop yield prediction are CNN and LSTM and DNN. The time-dependent information processing ability of LSTM makes this neural network variation from RNN especially valuable [18]. Multiple non-linear layer deep neural networks operate to extract information at all digital levels. The main use of deep neural networks includes identifying nonlinear relationships between input data and outcome measurements by implementing several hidden layers.

2.2 Deep Neural Network

The Deep Neural Networks (DNN) system shares a close relationship to traditional ANN algorithms through its fundamental methodology. The network topology of DNN and ANN includes numerous hidden layers which are fully connected to each other. CNN possesses different layer types because it embraces convolutional and pooling layers besides deep learning systems [19]. The Convolutional Neural Network (CNN) operates through its main structures located between the input and output layers which contain convolutional and pooling and activation stages. During input information processing the convolution layer operates local filters to execute convolution operations yet the pooling layer applies data reduction through max-pooling and average-pooling operations. Through non-linear operations activated by the activation layer CNN achieves better non-linear fitting properties. The weight updates within CNN follow a process that analogously functions as Backpropagation (BP) yet remains equivalent to the method used in Backpropagation Neural Networks (BPNN). LSTM operates as a Recurrent Neural Network version which utilizes gradient-based algorithms for recognizing temporal information in dataset sequences. The typical design of LSTM features an entrance layer which connects to at least one sequential LSTM layer that finally ends at an output layer. The RNN operates as a form of neural network by processing tabular data through sequences. The artificial neural network represents the time-dependent relationships among nodes through a directed graph structure [20]. RNN demonstrates an effective nature for sequence modeling which leads to better operational efficiency when processing sequence data. The machine learning method Transfer Learning applies previously trained models from one task to achieve successful outcomes when operating on related secondary tasks. The technique becomes valuable during limited labeled data situations since it enables us to take domain knowledge from one area and adapt it for another. The process of transfer learning in deep learning requires using pre-trained models with large datasets for subsequent training on new datasets and tasks according to. Model training becomes faster and more efficient because of this approach particularly when the new task contains restricted data.

2.3 Hybrid approach to crop yield prediction

Multiple ML and DL algorithms work together through common practices. The study by P. Sivanandhini et al. [21] used gradient boosting together with random forest and LASSO regression for creating localized crop yield forecasting models. Raja et al. developed a system that combined RF alongside Bagging and K-NN and SVM with DT and NB resulting in better accuracy levels when forecasting cereals and potatoes and energy crop yields. The prediction of maize yields through N. Nandhini et al. [22] involved integrating LR, Lasso Regression with RF and XG Boost and Light GBM. A. A. Alif et al. [23] integrated CNNs and FCNNs for winter wheat yield prediction. A. Fuentes et al. [24] combined CNN-LSTM, CNN-DNN, CNN-XGBoost, and CNN-RNN for soybean yield prediction. Future research should combine deep learning methods to resolve interpretability problems through fractional model and differential equation solution methods in crop yield prediction domains.

2.4 Performance evaluation metrics used in crop yield prediction analysis

Model estimation follows the essential process of evaluating simulation results against factual measurements. Evaluation metrics together with techniques used for evaluations are discussed in this segment. You must use evaluation metrics to properly measure model performance as they help distinguish different learning models. The calculation of average error significance with prediction arrays uses MAE that measures the average absolute value between forecasted and actual observation values [25]. The performance assessment of an estimator relies on MSE as it determines the closeness between regressor lines and their corresponding data points. The RMSE provides the standard deviation of the projected error by evaluating how well data points focus on the best fit line. The newly created framework demonstrates superior performance than the baseline framework based on the R-Squared coefficient that determines the data fit quality. The calculation of MAPE ascertains the average of percentage errors which represent the distance between model predictions and actual experimental results. Machine learning algorithms used for crop yield prediction perform assessments through the integration of precision by K. A. Shastry and H. A. Sanjay (2021) in [26] accompanied by accuracy metrics from 40 and 80 and recall evaluation from 59 and 97 and sensitivity evaluation from 34 and 43 and specificity evaluation from 80 and 97 and F1 Score evaluation by D. A. Bondre (2019) in [27]. The most frequently used metric and informative measure for classification problems is classification accuracy.

2.5 Practical Applications

Crop yield prediction models apply to numerous practical purposes in agricultural sectors. The models provide farmers with tools to arrange their resource utilization (water, fertilizer and pesticides) which results in higher yields at reduced operational expenses. Farmer Can Forecast Yield Variations Due to Environmental Factors to Put Risk Management Strategies in Place That Protect Their Farms from Harms of Adverse Weather or Environmental Stresses. Stakeholders profit from precise yield predictions by using them to develop informed plans that influence economic market operations and commodity prices while boosting market efficiency. The implementation of crop yield prediction models helps policymakers create verified programs which enhance rural development as well as sustainable agricultural practices and food security goals.

2.6 Recommendations for future research

Additional study is necessary to find the best crop yield prediction methods that take environmental aspects into account. The successful outcome of this project depends on choosing appropriate dataset entry and a meticulous pre-processing routine combined with optimal regression model training considering variable district environmental situations. Pre-trained models achieve better performance when they are fine-tuned with agricultural datasets especially under conditions of limited available labels [28]. The improvement of explainable features in DL models represents a necessary step to obtain farmer and stakeholder acceptance through building trust. The combination of data drawn from remote sensing and IoT devices as well as satellite imagery and weather data creates extensive agricultural system knowledge. Data fusion approaches of multiple modalities enable researchers to obtain critical findings while improving the functionality of ML and DL systems. The field of agricultural ML and DL requires combined efforts between researchers along with farmers along with agricultural extension services and policymakers to achieve advancement. The issuance of open data allows researchers to work with restricted agricultural datasets because these datasets become available to broader scientific groups. Consistent adoption of ML and DL models requires the development of models which demonstrate effective generalization throughout various environmental circumstances in addition to different croppings systems and geographic zones. The improvement of robustness in models can be achieved using data augmentation as well as ensemble learning and model regularization approaches. Successful adoption and impact requires ML and DL model design which places end-users at its forefront [29]. The model development becomes more effective when farmers and stakeholders provide input throughout the entire process to guarantee practical challenges will be solved with actionable findings. The summary demonstrates how crop yield prediction remains challenging and focuses on data quality choice of features and environmental conditions for achieving better accuracy results [30]. The application of ML and DL technology represents a transformative opportunity for agriculture since these systems create efficient farming systems alongside food security functions and environmental sustainability capabilities.

3. CONCLUSION

Advanced agricultural technologies represent an essential solution for overcoming the worldwide obstacle of nourishing a growing number of people on the planet. Modern agricultural practitioners need relevant and accurate predictions for crop yield estimation. Articles under analysis focus on two primary aspects concerning accessibility of utilized data and the scope of yield prediction through ML and DL technologies. Additional attributes in models do not demonstrate universally superior performance yet the selection process depends both on available dataset information and research targets. The studies deployed different sets of algorithms for their prediction work but each employed varying methods of utilization. Studies about yield prediction that utilize machine learning and deep learning techniques differ based on crop type together with geographical location and intensity measurement. A test of specific feature selection algorithms and high-performing models must identify the most efficient model through evaluation of machine learning model differences.

The machine learning analysis contains traditional frameworks including RF and SVM as well as NN. A review analyzes 47 research papers about deep learning algorithm methods. The three most preferred deep neural models include CNN alongside LSTM and DNN. Academic research shows that combination methods of pixel categorization with remote sensing data along with these techniques produce promising results for crop yield prediction. Predication accuracy grows stronger when researchers analyze quantitative and qualitative information sources including temperature facts and soil variations alongside remote sensing NDVI records. Regulating deep learning with remote sensing information and image processing algorithms leads to better predictions about crop outputs throughout extensive areas.

Weight-dependent yield estimation is used in multiple predictive models such as those based on crop analysis and ML and remote sensing technology. The process of count-based assessment through image processing and remote sensing modeling encounters difficulties with object clutter. The estimation of prediction accuracy uses common performance metrics which include four types of measurements: RMSE, R2, MAE and MSE alongside MAPE. Future studies on crop yield prediction require foundation from this research and center on developing deep learning-based analysis models. Specific testing of feature selection methods with predictive models should be combined with a solution for managing changing crop variables.

REFERENCES

[1] D. Diepeveen and L. Armstrong, “Identifying key crop performance traits using data mining” World Conference on Agriculture, Information and IT, 2008.

[2] Alexander Murynin, Konstantin Gorokhovskiy and Vladimir Ignatie “Efficiency of crop yield forecasting depending on the moment of prediction based on large remote sensing data set” retrieved from http://worldcomp-proceedings.com/proc/p2013/DMI8036.pdf

[3] F. H. Tseng, H. H.Cho, and H. T. Wu, “Applying big data for intelligent agriculture-based crop selection analysis,” IEEE Access, vol. 7, pp. 116965-116974, 2019.

[4] P. Tiwari, and P. Shukla, “Crop yield prediction by modified convolutional neural network and geographical indexes,” International Journal of Computer Sciences and Engineering, vol. 6, no. 8, pp. 503-513, 2018.

[5] A. Fuentes, S. Yoon, S. C. Kim, and D. S. Park, “A robust deeplearning-based detector for real-time tomato plant diseases and pests’ recognition,” Sensors, vol. 17, no. 9, pp. 2022, 2017.

[6] J. Sun, L, Di, Z. Sun, Y. Shen, and Z. Lai, “County-level soybean yield prediction using deep CNN-LSTM model,” Sensors, vol. 19, no. 20, pp. 4363, 2019.

[7] D. A. Bondre, and S. Mahagaonkar, “Prediction of Crop Yield and Fertilizer Recommendation Using Machine Learning Algorithms,” International Journal of Engineering Applied Sciences and Technology, vol. 4, no. 5, pp. 371-376, 2019.

[8] B. Devika, and B. Ananthi, “Analysis of crop yield prediction using data mining technique to predict annual yield of major crops,” International Research Journal of Engineering and Technology, vol. 5, no.12, pp. 1460-1465, 2018.

[9] V. Pandith, H. Kour, S. Singh, J. Manhas, and V. Sharma, “Performance Evaluation of Machine Learning Techniques for Mustard Crop Yield Prediction from Soil Analysis,” Journal of Scientific Research, vol. 64, no. 2, 2020.

[10] P. M. Gopal, and R. Bhargavi, “A novel approach for efficient crop yield prediction,” Computers and Electronics in Agriculture, vol. 165, pp. 104968, 2019.

[11] S. Khaki, and L. Wang, “Crop yield prediction using deep neural networks.” Frontiers in plant science, vol. 10, pp. 621, 2019.

[12] T. Vijayakumar, "Posed Inverse Problem Rectification Using Novel Deep Convolutional Neural Network,” Journal of Innovative Image Processing (JIIP), vol. 2, no. 03, pp. 121-127, 2020.

[13] T. Senthil Kumar, "Data Mining Based Marketing Decision Support System Using Hybrid Machine Learning Algorithm,” Journal of Artificial Intelligence, vol. 2, no. 03, pp. 185-193, 2020.

[14] R. Ghadge, J. Kulkarni, P. More, S. Nene and R. L. Priya, "Prediction of crop yield using machine learning", Int. Res. J. Eng. Technolgy, vol. 5, 2018.

[15] F. H. Tseng, H. H. Cho and H. T. Wu, "Applying big data for intelligent agriculture-based crop selection analysis", IEEE Access, vol. 7, pp. 116965-116974, 2019.

[16] A. Suresh, N. Manjunathan, P. Rajesh and E. Thangadurai, "Crop Yield Prediction Using Linear Support Vector Machine", European Journal of Molecular Clinical Medicine, vol. 7, no. 6, pp. 2189-2195, 2020.

[17] M. Alagurajan and C. Vijayakumaran, "ML Methods for Crop Yield Prediction and Estimation: An Exploration", International Journal of Engineering and Advanced Technology, vol. 9, no. 3, 2020.

[18] P. Kumari, S. Rathore, A. Kalamkar and T. Kambale, "Predicition of Crop Yeild Using SVM Approch with the Facility of E-MART System", Easychair, 2020.

[19] S. D. Kumar, S. Esakkirajan, S. Bama and B. Keerthiveena, "A microcontroller based machine vision approach for tomato grading and sorting using SVM classifier", Microprocessors and Microsystems, vol. 76, pp. 103090, 2020.

[20] P. Tiwari and P. Shukla, "Crop yield prediction by modified convolutional neural network and geographical indexes", International Journal of Computer Sciences and Engineering, vol. 6, no. 8, pp. 503-513, 2018.

[21] P. Sivanandhini and J. Prakash, "Crop Yield Prediction Analysis using Feed Forward and Recurrent Neural Network", International Journal of Innovative Science and Research Technology, vol. 5, no. 5, pp. 1092-1096, 2020.

[22] N. Nandhini and J. G. Shankar, "Prediction of crop growth using machine learning based on seed", Ictact journal on soft computing, vol. 11, no. 01, 2020.

[23] A. A. Alif, I. F. Shukanya and T. N. Afee, Crop prediction based on geographical and climatic data using machine learning and deep learning, 2018.

[24] A. Fuentes, S. Yoon, S. C. Kim and D. S. Park, "A robust deep-learning-based detector for real-time tomato plant diseases and pests recognition", Sensors, vol. 17, no. 9, pp. 2022, 2017.

[25] J. Sun, L. Di, Z. Sun, Y. Shen and Z. Lai, "County-level soybean yield prediction using deep CNN-LSTM model", Sensors, vol. 19, no. 20, pp. 4363, 2019.

[26] K. A. Shastry and H. A. Sanjay, "Hybrid prediction strategy to predict agricultural information", Applied Soft Computing, vol. 98, pp. 106811, 2021.

[27] D. A. Bondre and S. Mahagaonkar, "Prediction of Crop Yield and Fertilizer Recommendation Using Machine Learning Algorithms", International Journal of Engineering Applied Sciences and Technology, vol. 4, no. 5, pp. 371-376, 2019.

[28] B. Devika and B. Ananthi, "Analysis of crop yield prediction using data mining technique to predict annual yield of major crops", International Research Journal of Engineering and Technology, vol. 5, no. 12, pp. 1460-1465, 2018.

[29] V. Pandith, H. Kour, S. Singh, J. Manhas and V. Sharma, "Performance Evaluation of Machine Learning Techniques for Mustard Crop Yield Prediction from Soil Analysis", Journal of Scientific Research, vol. 64, no. 2, 2020.

[30] P. M. Gopal and R. Bhargavi, "A novel approach for efficient crop yield prediction", Computers and Electronics in Agriculture, vol. 165, pp. 104968, 2019.

[31] S. Khaki and L. Wang, "Crop yield prediction using deep neural networks", Frontiers in plant science, vol. 10, pp. 621, 2019.

[32] T. Vijayakumar, "Posed Inverse Problem Rectification Using Novel Deep Convolutional Neural Network", Journal of Innovative Image Processing (JIIP), vol. 2, no. 03, pp. 121-127, 2020.

[33] T. Senthil Kumar, "Data Mining Based Marketing Decision Support System Using Hybrid Machine Learning Algorithm", Journal of Artificial Intelligence, vol. 2, no. 03, pp. 185-193, 2020.

Author Profile:

Dr. N. Supriya is working as Associate Professor, in the department of Computer Science and Engineering (Data Science), School of Engineering, Malla Reddy University, Hyderabad. She is currently a Post-Doctoral Research Fellow at Department of Information systems and Decision Sciences at University of South Florida (USA). She obtained her M.Tech(CSE) and Ph.D(CSE) from ANU, Guntur. She published several papers in National and International Journals. She is active member of various professional bodies. Her current research is focused on Predictive Analytics, Cloud Computing and Software Reliability.

Prof. Bhuvan Unhelkar (Senior Member, IEEE) is a highly accomplished IT Professional and a Professor with the Muma School of Business, University of South Florida. He is also an Adjunct Professor with Western Sydney University and an Honorary Professor with Amity University, India. He is a Founding Consultant at MethodScience, with expertise in business analysis, software engineering, big data strategies, and AI. He is a winner of several prestigious awards, such as the Computerworld Object Developer Award in 1995, the Consensus IT Professional Award in 2006, and the IT Writer Award in 2010. He is a Fellow of the Australian Computer Society, an Associate Editor of IT Professional, and a Life Member of the Computer Society of India.

Prof. Pravin R. Kshirsagar is currently serving as a Professor for the Department of Electronics & Telecommunications Engineering, J D College of Engineering & Management, Nagpur, India. He has vast experience of 18 years in teaching. He has published various research articles in reputed journals. He has published more than 60 patents in national and international levels. He has six books in his credential. He is profoundly engrossed in data science, machine learning, artificial intelligence, and computer networks. He has also delivered special talks in national and international conferences and chaired various technical sessions in international conferences. He has served as a Reviewer for many international journals, such as Inderscience, Springer, Elsevier, and IEEE Transactions.

Prof Dr. Prasun Chakrabarti has received his Ph.D. (Engg) from Jadavpur University, India in 2009. He is working as Director, Directorate of Research and Publications and Dean International Affairs and Professor at Sir Padampat Singhania University, Udaipur, Rajasthan, India. He has more than 230 publications, 11 books and 42 filed Indian patents in his credit. He has supervised 10 Ph.D. candidates successfully. On various research assignments, he has visited Waseda University Japan (2012 availing prestigious INSA-CICS travel grant), University of Mauritius (2015), Nanyang Technological University Singapore (2015,2016,2019), Lincoln University College Malaysia (2018), National University of Singapore (2019), Asian Institute of Technology Bangkok Thailand (2019) and ISI Delhi (2019).

Dr.Shrikant V.Sonekar He is working as Professor and Principal in JD College of Engineering & Management, Nagpur, india. He has published more than 50 papers 10 books and 10 patents.

❖❖❖❖❖