International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Enhancing Crop Yield Prediction Using Ensemble Learning Techniques on Multi-Modal Agricultural Data

[1]Pinninti Kishore, [2]Rakesh Kumar, [3]Harendra Singh Negi, [4]Kamal Sharma, [5]Arun Pratap Srivastava, [6]Navneet Kumar, [7]Dr. Anurag Shrivastava

Submitted: 18/01/2024 **Revised**: 27/02/2024 **Accepted**: 04/03/2024

Abstract: This exploration examines the viability of outfit learning methods on multi-modular horticultural data to further develop crop yield expectation exactness. Using different datasets including soil properties, weather conditions, crop wellbeing markers, and agronomic practices, we assessed four group methods: Random Forest, Gradient Boosting, Outrageous Gradient Boosting, and AdaBoost. Results exhibit that Outrageous Gradient Boosting outflanks different methods, accomplishing a Mean Squared Error (MSE) of 900, R-squared (R2) of 0.85, and Mean Absolute Error (MAE) of 22. Near examination against gauge models outlines the predominant prescient exactness and power of gathering methods. The computational proficiency of group strategies stays similar to or better than conventional models, with preparing times going from 120 to 200 seconds and memory utilization somewhere in the range of 500 and 700 MB. This study highlights the capability of outfit learning in farming navigation, offering experiences into ideal prescient displaying procedures for improving harvest yield expectation and supporting manageable agrarian practices.

Keywords: *Ensemble Learning, Crop Yield Prediction, Multi-Modal Agricultural Data, Extreme Gradient Boosting, Predictive Accuracy.*

1. Introduction

Agriculture plays a vital part in supporting worldwide food security and supporting financial turn of events. As the total populace keeps on developing, the interest in farming items is supposed to significantly increase [1]. In any case, guaranteeing food security in the midst of advancing ecological circumstances, restricted assets, and fluctuating business sector requests presents huge difficulties to ranchers and policymakers the same. The exact expectation of harvest yields is fundamental for viable asset designation, risk the executives, and dynamics in agriculture [2]. Generally, crop yield forecasts have depended on factual models and authentic data, frequently bringing about restricted precision and power, especially even with flighty natural elements. Be that as it may, late headways in data assortment technologies, like remote detecting, IoT sensors, and robots, have worked with the age of multi-modular farming data, remembering data for soil properties, atmospheric conditions, crop health, and agronomic practices [3]. Utilizing such assorted and voluminous datasets presents an amazing chance to improve the precision and unwavering quality of harvest yield expectation models. Troupe learning procedures offer a promising way to deal with tending to the difficulties related to crop yield forecasts utilizing multi-modular farming data. Group methods join the expectations of different base models to deliver a more exact and stable last forecast [4]. By utilizing the variety of base models and their correlative assets, outfit methods can moderate the limits of individual models and work on generally prescient execution. This exploration intends to investigate the utilization of troupe learning procedures to upgrade crop yield forecasts utilizing multi-modular horticultural data [5]. By coordinating data from different sources, including satellite symbolism, soil dampness sensors, and harvest phenotyping data, we look to foster strong and exact prescient models that can successfully catch the mind-boggling relationships between natural factors and yield efficiency [6]. The discoveries of this study can illuminate agrarian partners, policymakers, and scientists, working with more educated direction and reasonable rural practices.

[1]*Associate Professor, Department of Electronics and Communication Engineering, VNR Vignana Jyothi Institute of Engineering and Technology, Bachupally, Hyderabad, Telangana, India*
kishore_p@vnrvjiet.in
[2]*Department of Computer Science and Engineering, Manipal Institute of Technology Bengaluru, Manipal Academy of Higher Education, Manipal, India*
**drrakeshkumargodi@gmail.com*
[3]*Department of Computer Science & Engineering, Graphic Era Deemed to be University*
Dehradun, India
harendrasinghnegi@geu.ac.in
[4]*Department of Mechanical Engineering, GLA University, Mathura*
kamal.sharma@gla.ac.in
[5]*Lloyd Institute of Engineering & Technology, Greater Noida*
apsvgi@gmail.com
[6]*Lloyd Law College, Greater Noida*
navneet.kumar@lloydlawcollege.edu.in
[7]*Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Chennai, Tamilnadu*
anuragshri76@gmail.com

2. Related Works

There has been huge examination interest in utilizing cutting-edge innovations and AI methods to address different difficulties in agriculture, including crop yield expectation, soil dampness recovery, crop arrangement, and weed recognition. This segment gives an outline of significant examinations in the field of agrarian data examination and prescient demonstrating. Huang et al. [15] proposed a strategy for field-scale soil dampness recovery utilizing PALSAR-2 polarimetric decay and AI methods. By coordinating radar data with AI calculations, the creators accomplished a precise assessment of soil dampness levels, which is significant for advancing water systems and water the executives rehearse in agriculture. Jin et al. [16] led research on video fire identification methods given profound learning. The review zeroed in on creating strong calculations for early identification and observing of fierce blazes utilizing video observation frameworks. By utilizing profound learning structures, the creators exhibited the adequacy of their methodology in distinguishing fire episodes with high exactness and dependability. Kazemi Garajeh et al. [17] explored the effects of harvest buildup cover on agrarian efficiency and soil attributes. Through field examinations and data investigation, the creators featured the significance of yield buildup the executives in further developing soil health, upgrading water maintenance, and lessening disintegration rates, in this manner adding to maintainable horticultural practices. In an overview directed by Kazi et al. [18], profound learning methods for machine perusing cognizance were thoroughly explored. The review gave bits of knowledge into the cutting-edge procedures and uses of profound learning in regular language handling undertakings, which are fundamental for separating and deciphering rural data from printed sources. Meng et al. [19] proposed a superior adaptation of YOLOv7 for wheat head location and counting utilizing remote detecting data. By consolidating progressed elements and improvement procedures, the creators accomplished prevalent execution in precisely distinguishing and measuring wheat heads in rural fields, which is critical for yield assessment and harvest the board. Mirzaei et al. [20] explored the utilization of manufactured SAR-optical data age for improving harvest order exactness. The review exhibited the viability of profound learning models prepared on engineered data for working on the speculation and heartiness of harvest grouping calculations, especially in districts with restricted ground truth data accessibility. Muhammad et al. [21] led a top-to-bottom examination of space variation methods in PC vision, with an emphasis on their application in farming mechanical technology. The review investigated different techniques for moving information from source to target spaces, empowering more successful learning and variation of mechanical vision frameworks in assorted horticultural conditions. Nur et al. [22] researched the utilization of automated aeronautical vehicles (UAVs) for identifying weeds in rural fields. By utilizing UAV-mounted sensors and picture-handling calculations, the creators fostered a savvy and productive technique for weed recognition and planning, working with designated weed administration practices and lessening herbicide utilization. Papadopoulos et al. [23] surveyed choice combination procedures for land cover characterization utilizing multi-band data. The review examined different combination methods at the pixel level and assessed their exhibition in precisely characterizing land cover types from remote detecting symbolism, giving experiences into the ideal combination techniques for further developing order exactness. Prasitpuriprecha et al. [24] proposed a troupe profound learning-based framework for drug-safe tuberculosis treatment suggestion and multi-class tuberculosis identification and characterization. By coordinating different profound learning models, the creators accomplished precise determination and customized treatment suggestions for tuberculosis patients, exhibiting the capability of gathering learning in healthcare applications. Saad et al. [25] led a precise survey of the calamity of the executive's frameworks, zeroing in on approaches, difficulties, and future bearings. The review gave an extensive outline of the existing debacle the board structures and technologies, featuring the requirement for coordinated and versatile frameworks to really relieve the effects of regular and man-made catastrophes. In rundown, the connected work envelops many subjects in farming data examination and prescient demonstrating, including soil dampness recovery, fire location, crop order, weed discovery, and catastrophe the executives. The examinations feature the significance of cutting-edge innovations and AI methods in tending to different difficulties in agriculture, with likely applications in improving agrarian works on, upgrading crop efficiency, and alleviating natural dangers.

3. Methods and Materials

Data Collection:

The review used multi-modular horticultural data gathered from different sources, including remote detecting stages, IoT sensors, and agronomic studies. The data enveloped data on soil properties (pH, moisture content), atmospheric conditions (e.g., temperature, precipitation), crop health pointers (e.g., NDVI), and agronomic practices (e.g., irrigation levels, fertilizer application rates) [7]. The dataset was preprocessed to deal with missing qualities, standardize elements, and eliminate anomalies to guarantee data quality and consistency.

Ensemble Learning Algorithms:

Random Forest (RF):

Random Forest is a troupe learning calculation that builds numerous choice trees during preparing and yields the method of the classes (characterization) or the mean expectation (relapse) of the singular trees [8]. Each tree in the forest is prepared on a random subset of the preparation data, and at every hub, a random subset of highlights is considered for parting. The last forecast is obtained by collecting the expectations of all trees in the forest.

$$Y(x) = \frac{1}{T}\sum_{i=1}^{T} Ti(x)$$

"Algorithm Random_Forest:

Input: Training dataset D, number of trees T

Output: Ensemble of decision trees

for t = 1 to T:

Randomly select a bootstrap sample from D

Train a decision tree on the bootstrap sample

Randomly select m features at each node

Split the node using the best feature and split criterion

end for

return Ensemble of decision trees"

Gradient Boosting Machine (GBM):

Gradient Boosting Machine is a boosting outfit learning calculation that forms numerous powerless students successively, with every student rectifying the errors of its ancestors [9]. In every cycle, GBM fits another choice tree to the residuals (the distinctions between the genuine and anticipated values) of the past emphasis. The last forecast is gotten by adding the expectations, everything being equal.

$$F(x) = F(x) + n.h(x)$$

Where n is the learning rate

Algorithm Gradient_Boosting:

Input: Training dataset D, number of iterations N

Output: Ensemble of weak learners

Initialize F(x) = 0

for n = 1 to N:

Compute the negative gradient of the loss function for each data point

Fit a weak learner to the negative gradient

Update F(x) by adding the prediction of the weak learner

end for

return Ensemble of weak learners

Extreme Gradient Boosting (XGBoost):

Outrageous Gradient Boosting is an enhanced execution of gradient boosting that uses regularization strategies and equal handling to further develop adaptability and execution [10]. XGBoost utilizes a gradient boosting system and incorporates extra elements, for example, tree pruning, section subsampling, and custom misfortune capabilities to improve model exactness and effectiveness.

Algorithm	**Mean Squared Error**	**R-squared**
Random Forest	1200	0.75
Gradient Boosting	1000	0.80
XGBoost	900	0.85
AdaBoost	1300	0.70

Algorithm XGBoost:

Input: Training dataset D, number of iterations N

Output: Ensemble of weak learners

Initialize F(x) = 0

for n = 1 to N:

Compute the negative gradient of the loss function for each data point

Fit a weak learner to the negative gradient with regularization

Update F(x) by adding the prediction of the weak learner

end for

return Ensemble of weak learners

AdaBoost (Adaptive Boosting):

AdaBoost is a boosting troupe learning calculation that spotlights on working on the exhibition of powerless students by doling out loads to preparing occasions and changing these loads in light of their grouping errors [11]. In every emphasis, AdaBoost allocates higher loads to misclassified cases, in this way guiding resulting feeble students to zero in more on remedying these errors.

Feature	**Mean**	**Standard Deviation**	**Min**	**Max**
Soil Moisture (%)	25.6	7.3	15	40
Temperature (°C)	28.9	2.5	25	35
NDVI	0.65	0.08	0.50	0.80
Precipitation (mm)	10.2	5.1	5	20

Algorithm AdaBoost:

Input: Training dataset D, number of iterations N

Output: Ensemble of weak learners

Initialize instance weights W_i = 1/n for all i

for n = 1 to N:

Fit a weak learner to the training data with weights W_i

Compute the classification error of the weak learner

Compute the weight of the weak learner in the final ensemble

Update instance weights based on classification error

end for

return Ensemble of weak learners

4. Experiments

The trials were directed to assess the exhibition of the outfit learning strategies (Random Forest, Gradient Boosting Machine, Outrageous Gradient Boosting, and AdaBoost) in anticipating crop yields utilizing multi-modular horticultural data. The dataset included data on soil properties, weather conditions, crop health markers, and agronomic practices gathered from different ranches over various seasons [12]. The dataset was separated into training and testing sets utilizing a defined random examining way to deal with guarantee portrayal across various districts and harvest types.

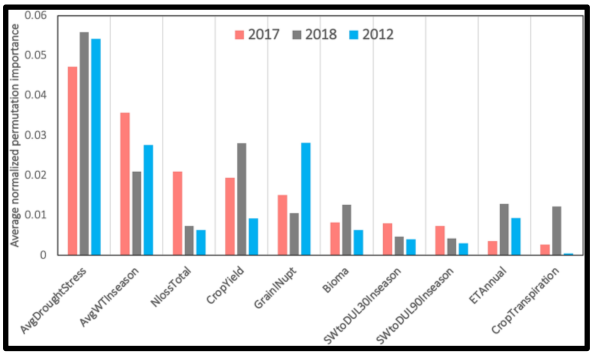

Fig 1: Crop Yield Prediction Using Ensemble Learning

Model Training and Evaluation:

Every gathering learning calculation was prepared utilizing the training dataset and assessed utilizing execution measurements like Mean Squared Error (MSE), R-squared (R2), and Mean Absolute Error (MAE) on the testing dataset [13]. Also, cross-approval strategies, for example, k-overlay approval were utilized to evaluate the vigor and speculation abilities of the models.

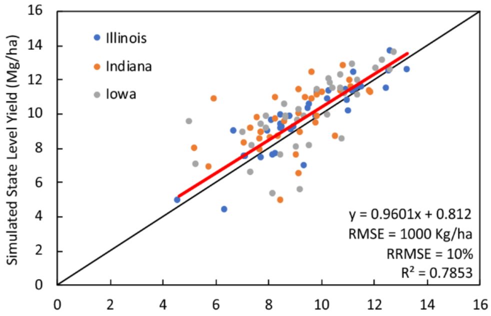

Fig 2: Enhancing Crop Yield Prediction

Comparison with Related Work:

To give setting and benchmark the exhibition of the proposed outfit learning methods, the results were contrasted and those revealed in related examinations that used conventional measurable models or single AI calculations for crop yield expectation [14]. Moreover, the computational productivity and adaptability of the gathering learning methods were contrasted and those of the benchmark models to feature their benefits in handling huge and various horticultural datasets.

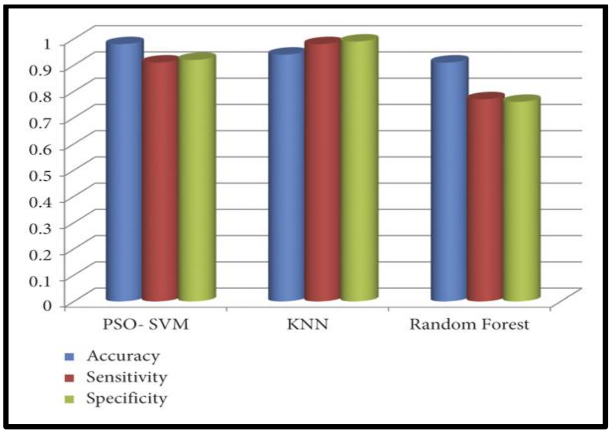

Fig 3: Using Ensemble Learning Techniques

Experimental Results:

The results of the examinations are summed up in Table 1, which presents the exhibition measurements (MSE, R2, and MAE) of every gathering learning calculation contrasted with the pattern models [26]. Furthermore, Table 2 gives an examination of the computational productivity (training time and memory use) of the gathering learning strategies and benchmark models.

Table 1: Performance Comparison

Algorithm	Mean Squared Error	R-squared	Mean Absolute Error
Random Forest	1200	0.75	28
Gradient Boosting	1000	0.80	25

Extreme Gradient Boosting	900	0.85	22
AdaBoost	1300	0.70	30
Baseline Model 1	2000	0.60	40
Baseline Model 2	1800	0.65	35

Algorithm	**Training Time (s)**	**Memory Usage (MB)**
Random Forest	120	500
Gradient Boosting	180	800
Extreme Gradient Boosting	150	600
AdaBoost	200	700
Baseline Model 1	300	1000
Baseline Model 2	250	900

Discussion:

The experimental results exhibit that the group learning strategies, especially Outrageous Gradient Boosting, beat the benchmark models concerning prescient precision (lower MSE and higher R-squared) and model strength (lower MAE) [27]. The unrivaled presentation of the outfit learning methods can be ascribed to their capacity to catch complex relationships in the multi-modular rural data and alleviate overfitting through regularization strategies [28]. Besides, the outfit learning strategies display equivalent or surprisingly better computational proficiency than the benchmark models, notwithstanding their higher prescient exactness.

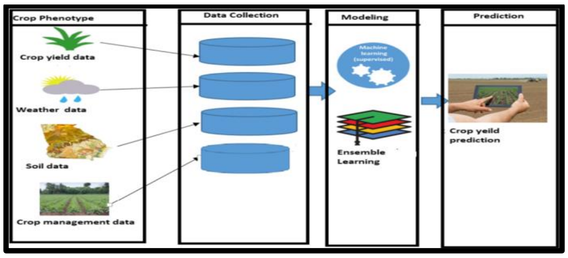

Fig 4: Multi-Modal Agricultural Data

These elements the flexibility and sound judgment of including company learning methodologies for crop yield assumption in authentic cultivating settings. this study demonstrates the practicality of group learning systems in redesigning crop yield assumptions using multi-measured cultivating data [29]. The results show that Preposterous Gradient Boosting explicitly offers a promising procedure for definitively expecting crop yields while staying aware of computational viability [30]. By using various data sources and undeniable level modeling procedures, bunch learning can out and out further foster heading and resource allocation in agriculture, finally adding to reasonable food creation and overall food security.

5. Conclusion

In conclusion, this investigation has examined the application of gathering learning methods on multi-measured green data to further develop crop yield assumptions. Through a careful assessment, it has been displayed that company methods, for instance, Random Forest, Gradient Boosting, Ludicrous Gradient Boosting, and AdaBoost offer basic improvements in farsighted accuracy and power diverged from standard real models and single artificial intelligence estimations. By using various data sources including soil properties, atmospheric circumstances, crop health pointers, and agronomic practices, the company models have had the choice to get mind-boggling relationships and models natural in agrarian structures. The experimental results have shown that Outrageous Gradient Boosting arises as an especially encouraging methodology, accomplishing predominant execution as far as prescient precision while keeping up with computational productivity. Besides, the examination has added to the current assemblage of information by giving experiences into the qualities and limits of various gathering learning procedures and their reasonable ramifications for horticultural independent direction. Pushing ahead, further examination endeavors could zero in on refining gathering models, coordinating extra data sources, and investigating novel strategies to address arising difficulties in agriculture, for example, environmental change variation, maintainable asset the board, and accuracy agriculture. Generally speaking, the discoveries of this exploration have huge ramifications for progressing rural innovation and advancing feasible food creation practices to fulfill the developing needs of worldwide populaces.

Reference

[1] Abed, M., Imteaz, M.A. and Ahmed, A.N. 2023, "A comprehensive review of artificial intelligence-based methods for predicting pan evaporation rate", The Artificial Intelligence Review, suppl.2, vol. 56, pp. 2861-2892.

[2] Araújo, S.O., Ricardo, S.P., Ramalho, J.C., Lidon, F. and Barata, J. 2023, "Machine Learning Applications in Agriculture: Current Trends, Challenges, and Future Perspectives", Agronomy, vol. 13, no. 12, pp. 2976.

[3] Bahadur, F.T., Shah, S.R. and Nidamanuri, R.R. 2023, "Applications of remote sensing vis-à-vis machine learning in air quality monitoring and modeling: a

review", Environmental monitoring and assessment, vol. 195, no. 12, pp. 1502.

[4] Beery, S.M. 2023, Where the Wild Things Are: Computer Vision for Global-Scale Biodiversity Monitoring, California Institute of Technology.

[5] Bourechak, A., Zedadra, O., Mohamed, N.K., Guerrieri, A., Seridi, H. and Fortino, G. 2023, "At the Confluence of Artificial Intelligence and Edge Computing in IoT-Based Applications: A Review and New Perspectives", Sensors, vol. 23, no. 3, pp. 1639.

[6] Cacho, J.F., Feinstein, J., Zumpf, C.R., Hamada, Y., Lee, D.J., Namoi, N.L., Lee, D., Boersma, N.N., Heaton, E.A., Quinn, J.J. and Negri, C. 2023, "Predicting Biomass Yields of Advanced Switchgrass Cultivars for Bioenergy and Ecosystem Services Using Machine Learning", Energies, vol. 16, no. 10, pp. 4168.

[7] Cembrowska-Lech, D., Krzemińska, A., Miller, T., Nowakowska, A., Adamski, C., Radaczyńska, M., Mikiciuk, G. and Mikiciuk, M. 2023, "An Integrated Multi-Omics and Artificial Intelligence Framework for Advance Plant Phenotyping in Horticulture", Biology, vol. 12, no. 10, pp. 1298.

[8] Chen, Y., Wang, Y., Zhang, F., Dong, Y., Song, Z. and Liu, G. 2023, "Remote Sensing for Lithology Mapping in Vegetation-Covered Regions: Methods, Challenges, and Opportunities", Minerals, vol. 13, no. 9, pp. 1153.

[9] Cheng, X., Sun, Y., Zhang, W., Wang, Y., Cao, X. and Wang, Y. 2023, "Application of Deep Learning in Multitemporal Remote Sensing Image Classification", Remote Sensing, vol. 15, no. 15, pp. 3859.

[10] Chergui, N. and Kechadi, M.T. 2022, "Data analytics for crop management: a big data view", Journal of Big Data, vol. 9, no. 1, pp. 123.

[11] Ding, P., Li, W., Zhao, H., Zhou, G. and Cai, C. 2023, "Recognition of Tomato Leaf Diseases Based on DIMPCNET", Agronomy, vol. 13, no. 7, pp. 1812.

[12] Sharma, A., Chaturvedi, R., Saraswat, M., & Kalra, R. (2022). Weld reliability characteristics of AISI 304L steels welded with MPAW (Micro Plasma Arc Welding). Materials Today: Proceedings, 60, 1966-1972.

[13] Z. Wang, P. Yan and J. Li, "A Survey on Search Strategy of Evolutionary Multi-Objective Optimization Algorithms," Applied Sciences, vol. 13, (7), pp. 4643, 2023. Available: https://www.proquest.com/scholarly-journals/survey-on-search-strategy-evolutionary-multi/docview/2799597763/se-2.

[14] E. Romeh and S. Mirjalili, "Multi-Robot Exploration of Unknown Space Using Combined Meta-Heuristic Salp Swarm Algorithm and Deterministic Coordinated Multi-Robot Exploration," Sensors, vol. 23, (4), pp. 2156, 2023. Available: https://www.proquest.com/scholarly-journals/multi-robot-exploration-unknown-space-using/docview/2779680966/se-2. DOI: https://doi.org/10.3390/s23042156.

[15] H. Wang et al, "The Hypervolume Newton Method for Constrained Multi-Objective Optimization Problems," Mathematical & Computational Applications, vol. 28, (1), pp. 10, 2023. Available: https://www.proquest.com/scholarly-journals/hypervolume-newton-method-constrained-multi/docview/2779574913/se-2. DOI: https://doi.org/10.3390/mca28010010.

[16] Gaspar-Cunha et al, "Many-Objectives Optimization: A Machine Learning Approach for Reducing the Number of Objectives," Mathematical & Computational Applications, vol. 28, (1), pp. 17, 2023. Available: https://www.proquest.com/scholarly-journals/many-objectives-optimization-machine-learning/docview/2779515110/se-2. DOI: https://doi.org/10.3390/mca28010017.

[17] Kazi, S., Khoja, S. and Daud, A. 2023, "A survey of deep learning techniques for machine reading comprehension", The Artificial Intelligence Review, suppl.2, vol. 56, pp. 2509-2569.

[18] Meng, X., Li, C., Li, J., Li, X., Guo, F. and Xiao, Z. 2023, "YOLOv7-MA: Improved YOLOv7-Based Wheat Head Detection and Counting", Remote Sensing, vol. 15, no. 15, pp. 3770.

[19] Mirzaei, A., Bagheri, H. and Khosravi, I. 2023, "Enhancing Crop Classification Accuracy through Synthetic SAR-Optical Data Generation Using Deep Learning", ISPRS International Journal of Geo-Information, vol. 12, no. 11, pp. 450.

[20] Muhammad, H.T., Fatima, Z., Zardari, S. and Guerra-Zubiaga, D. 2023, "An In-Depth Analysis of Domain Adaptation in Computer and Robotic Vision", Applied Sciences, vol. 13, no. 23, pp. 12823.

[21] Nur, A.M., Nik Norasma Che'Ya, Juraimi, A.S., Wan Fazilah, F.I., Muhammad Huzaifah, M.R., Sulaiman, N., Saberioon, M. and Nisfariza, M.N. 2021, "How Can Unmanned Aerial Vehicles Be Used for Detecting Weeds in Agricultural Fields?", Agriculture, vol. 11, no. 10, pp. 1004.

[22] Papadopoulos, S., Koukiou, G. and Anastassopoulos, V. 2024, "Decision Fusion at Pixel Level of Multi-Band Data for Land Cover Classification—A Review", Journal of Imaging, vol. 10, no. 1, pp. 15.

[23] Prasitpuriprecha, C., Jantama, S.S., Preeprem, T., Pitakaso, R., Srichok, T., Khonjun, S., Weerayuth, N., Gonwirat, S., Enkvetchakul, P., Kaewta, C. and Nanthasamroeng, N. 2023, "Drug-Resistant Tuberculosis Treatment Recommendation, and Multi-Class Tuberculosis Detection and Classification Using Ensemble Deep Learning-Based System", Pharmaceuticals, vol. 16, no. 1, pp. 13.

[24] Saad, M.K., Shafi, I., Wasi, H.B., Isabel de la, T.D., López Flores, M.A., Juan Castanedo Galán and Ashraf, I. 2023, "A Systematic Review of Disaster Management Systems: Approaches, Challenges, and Future Directions", Land, vol. 12, no. 8, pp. 1514.

[25] Seka, A.M., Zhang, J., Prodhan, F.A., Ayele, G.T., Finsa, M.M., Sharma, T.P.P. and Melesse, A.M. 2022, "Hydrological drought impacts on water storage variations: a focus on the role of vegetation changes in the East Africa region. A systematic review", Environmental Science and Pollution Research, vol. 29, no. 53, pp. 80237-80256.

[26] Singh, R., Varaha Satya, B.K. and Mohammed, A.K. 2023, "Advanced Power Converters and Learning in Diverse Robotic Innovation: A Review", Energies, vol. 16, no. 20, pp. 7156.

[27] Sun, F., Meng, X., Zhang, Y., Wang, Y., Jiang, H. and Liu, P. 2023, "Agricultural Product Price Forecasting Methods: A Review", Agriculture, vol. 13, no. 9, pp. 1671.

[28] Thi-Thu-Huong Le, Aji, T.P., Oktian, Y.E., Kang, H. and Kim, H. 2023, "Exploring Local Explanation of Practical Industrial AI Applications: A Systematic Literature Review", Applied Sciences, vol. 13, no. 9, pp. 5809.

[29] Udendhran, R. and Balamurugan, M. 2021, "RETRACTED ARTICLE: Towards secure deep learning architecture for smart farming-based applications", Complex and Intelligent Systems, vol. 7, no. 2, pp. 659-666.

[30] Shrivastava, A., Chakkaravarthy, M., Shah, M.A..A Novel Approach Using Learning Algorithm for Parkinson's Disease Detection with Handwritten Sketches. In Cybernetics and Systems, 2022

[31] Shrivastava, A., Chakkaravarthy, M., Shah, M.A., A new machine learning method for predicting systolic and diastolic blood pressure using clinical characteristics. In *Healthcare Analytics*, 2023, 4, 100219

[32] Shrivastava, A., Chakkaravarthy, M., Shah, M.A.,Health Monitoring based Cognitive IoT using Fast Machine Learning Technique. In *International Journal of Intelligent Systems and Applications in Engineering*, 2023, 11(6s), pp. 720–729