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A Novel Method For Air Quality-Driven Crop Prediction In Aeroponic Farming

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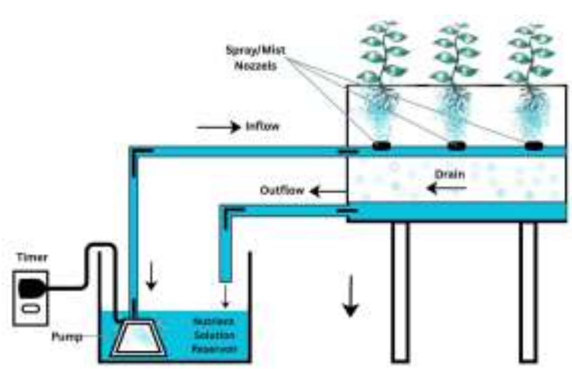
Abstract: Traditional farming practices are not long-term viable due to the growing freshwater shortage and diminishing soil fertility, which pose serious threats to global food security. Because it eliminates soil-borne diseases, uses up to 95% less water, and supports sustainable development goals, aeroponic farming is a soilless cultivation method that emerges as an effective substitute. However, crop productivity in aeroponics is highly dependent on the quality of the surrounding air, in contrast to soil-based agriculture, where yield is determined by the fertility of the soil. In order to predict crop suitability in aeroponic systems, this paper proposes a novel methodology that combines the Air Quality Index (AQI) with real-time air pollutant concentrations of PM2.5, PM10, NO2, CO, and SO2. Based on scientific literature, AQI values and pollutant thresholds were mapped to crop tolerance levels to create a custom dataset. The suggested system uses a Random Forest classifier to suggest crops that are most suited to the local air conditions, calculates AQI using the US-EPA formula, and processes pollutant inputs. The model performs reliably, achieving 80% prediction accuracy while remaining robust to noisy data inputs. The study presents a scalable, flexible framework for crop selection that promotes sustainable agriculture and emphasizes the significance of air quality as a crucial component of soilless farming. In order to further improve reliability, future scope will involve adding more crops, incorporating environmental variables like temperature and humidity, and cross-referencing predictions with yield data collected at the field level.

Keywords: Aeroponics, Crop Prediction, Crop Yield, Air Quality, Machine Learning.

I. INTRODUCTION:

As it is well known, the Earth's freshwater level is rapidly declining these days, and excessive fertilizer use is rendering the soil infertile [1] [2]. The quality and quantity of the crop are solely dependent on soil fertility, and traditional farming needs a lot of water to keep the soil moist [3]. Managing these soil and water problems while producing enough food for the world's growing population is the largest challenge facing farmers [4] [5] [6]. Farmers are finding it difficult to deal with these problems in traditional farming [7]. Aeroponic farming is a contemporary farming method that solves the above-mentioned issues in this case [8] [9].

Compared to conventional farming, aeroponics uses very little water and no soil when growing crops [10]. The plants are cultivated in a sealed chamber in an aeroponics system [11] [12]. In order to shield the plant roots from direct sunlight and to prevent the growth of algae [13], the plant sprouts are first removed and placed inside the chamber, which is covered with a black plastic sheet [14]. The plant's roots will dangle freely within the growth chamber [15].



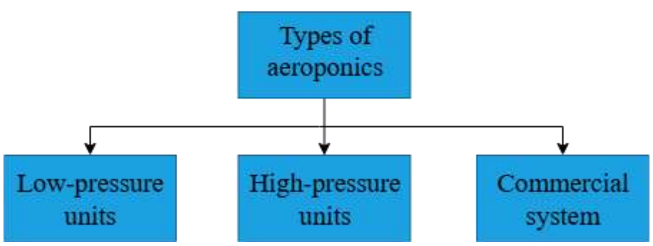
Aeroponic Farming (Fig. 1)

This method involves continuously spraying the roots with a nutrient solution, a mixture of dissolved nutrients and minerals necessary for the plants' healthy growth, to keep them moist [16]. A drip-back system returns any extra or unused nutrient solution to the main tank. Fig. 1 explains the entire structure of aeroponic farming [17] [18].

According to studies, aeroponic plants can lower pollutants such as volatile organic compounds (VOCs) by about 20%, nitrogen oxides by about 4%, carbon components by about 28%, and particulates by about 27%. Compared to conventional farming, air farming uses 95% less water. Aeroponics eliminates the need for soil, so it helps prevent soil-borne illnesses [19] [20]. By enhancing food production, aeroponics helps achieve SDG 2 (Zero Hunger). It also helps achieve SDG 13 (Climate Action) by lowering the carbon footprint of agriculture from transporting yields from one location to another, and SDG 6 (Clean Water and Sanitation) by using less water [21]. Fig 2 explains the types of aeroponic farming systems.

Types of Aeroponic Farming based on the watering:

1. **Low-Pressure Units**
2. **High-Pressure Units**
3. **Commercial System**



Types of Aeroponic Farming (Fig. 2)

Low-pressure units: The roots of the plants in the majority of low-pressure aeroponic gardens hang over a reservoir that holds nutritional solution or are connected to a reservoir by an internal channel [22]. A low-pressure pump supplies the nutritional solution via jets or ultrasonic transducers, which subsequently return the nutrients to the reservoir by dripping or draining them [23]. As plants get older, they develop dry patches in their root systems that make it difficult for them to take in enough nutrients [24] [25]. Due to their high cost, these devices are unable to remove undesired bacteria or debris or clean the nutrient solution. Bench-top growth is typically acceptable for these units. Aeroponics is also demonstrated with them [26].

High-pressure units: In high-pressure aeroponic devices, mist is produced by a high-pressure pump [27]. High-value crops are typically produced using this technique [28]. It uses technologies for water purification, nutrient sterilization, low-oxygen air, low-mass polymers, and pressured nutrient delivery systems [29].

Commercial system: The commercial system makes use of hardware for high-pressure devices as well as biological systems [30]. The matrix of biological systems encourages faster crop maturation and longer plant life [31]. The crop yield in aeroponics is dependent on the air quality in which it will be grown, just as it is in traditional farming, which depends on the fertility of the soil [32]. The crop yield is significantly influenced by the air quality in the area where will be conducting air farming [33]. Air elements that affect plant growth include carbon dioxide (CO_2), oxygen (O_2), ozone (O_3), nitrogen dioxide (NO_2), sulfur dioxide (SO_2), particulate matter ≤2.5/10 microns (PM2.5/PM10), humidity, and volatile organic compounds (VOCs).

II. LITERATURE SURVEY:

The modernization of agriculture has been greatly aided by recent developments in artificial intelligence (AI), machine learning (ML), and the internet of things (IoT), especially in fields like crop yield prediction, smart irrigation, fertigation, and aeroponics [34]. Numerous studies have put forth models and systems to increase sustainability, accuracy, and productivity. An overview of the main findings from recent studies is provided below.

ML models for crop selection and cultivation prediction were created by T. Deshmukh et al. [3]. Their system improves overall productivity by helping farmers select the right crops. However, the calibre and accessibility of input data have a significant impact on how well their models work.

S. Thirumal and R. Latha et al. [4] combined the Sine Cosine Algorithm (SCA) with a Weighted Regularized Extreme Learning Machine (WRELM) to predict rice yield in a more sophisticated machine learning application [35]. Although their method required large datasets for optimal performance and came at the cost of computational complexity, it demonstrated high accuracy in handling non-linear agricultural data [36].
K. Xiao et al. [6] used big data in agriculture to detect and predict crop growth. Big data made it easier to analyze trends and make well-informed decisions, but it also created a need for reliable infrastructures for data collection [37].

In order to improve prediction accuracy across multiple Indian states, V. K. et al. [7] combined ML models with power transformation techniques [38]. Although performance was enhanced, this method presented difficulties with model interpretability and climate change adaptation [39].

Similarly, a general machine learning (ML) based crop yield prediction system was proposed by R. J. et al. [9] and proved useful in agricultural planning. However, when dealing with incomplete or missing datasets, the model's accuracy decreased [40].

A comparative analysis of different machine learning techniques for crop yield prediction was conducted by T. Anitha et al. [10]. By identifying successful models, the results promote sustainable agriculture; however, for continued accuracy, they need to be regularly retrained using updated datasets [41].

Aeroponic system integration of AI and IoT has also become more popular. In their review of the application of AI and plasma-based high-efficiency tools in smart aeroponics, W. A. Qureshi et al. [11] emphasized increased system efficiency. However, the implementation and maintenance of such systems are costly and complex [42].

L. A. Damian-Damian et al. [12] used the ESP32 microcontroller to design a nutrient spray system, offering a workable and affordable solution. Although effective for small-scale applications, hardware limitations still limit its scalability.

In order to regulate spraying in aeroponic systems, A. D. Salsabila et al. [13] employed logistic regression. Although the model is simple to understand and appropriate for real-time monitoring, it might not work well with intricate agricultural datasets.

A. U. Rehman et al. [14] also investigated IoT-based smart aeroponic systems, emphasizing automated control, real-time monitoring, and economical resource use. Although advantageous, the system's dependence on power and network stability may present difficulties.
S. Setiawati et al. [15] looked into fertilization control using fuzzy logic, using Sugano's fuzzy logic to deal with nutrient delivery uncertainty. Although this system provides flexible and adaptive control, the creation of rules necessitates domain expertise.

III. METHODOLOGY

The proposed methodology can be used to assess a crop's suitability for air factors like particulate matter ≤2.5/10 microns (PM2.5/PM10), sulphur dioxide (SO2), nitrogen dioxide (NO2), and carbon monoxide (CO). Since the air quality in the area where intend to conduct air farming directly affects the crop yield in the aerophones, want to suggest a crop (Chili, Groundnut, Rice) that will yield more. developed a model that allows users to enter the current local concentrations of SO2, CO, NO2, PM2.5, and PM10 in real time. This input can be gathered via manual entry, publicly available datasets, or local monitoring sensors, ensuring flexible adoption regardless of the degree of digital infrastructure. The input values' validity, completeness, and sensor anomalies are investigated. To prevent inaccurate predictions, outlier detection and simple normalization are used. If necessary, missing values can be estimated using recent historical data or flagged for user attention. Each pollutant's Air Quality Index (AQI) is determined using the US-EPA formula:

$$\mathrm{Ip} = \left(\frac{\mathrm{I_{Hi}} - \mathrm{I_{Lo}}}{\mathrm{BP_{Hi}} - \mathrm{BP_{Lo}}}\right)(\mathrm{Cp} - \mathrm{BP_{Lo}}) + \mathrm{I_{Lo}} \quad (1)$$

Ip: Pollutant p index value
Cp: Pollutant p concentration
BPLo and BPHi: Breakpoint concentrations slightly above and below Cp

The maximum sub-index for all pollutants at a given location is the final AQI:

$$AQI = \max_{p}\{I_p\} \quad (2)$$

AQI values for those breakpoints are IHi and ILo.
For each pollutant (PM2.5, PM10, NO2, CO, SO2), the formula is applied individually with pollutant-specific breakpoints from official AQI tables. The location's final AQI, which represents the predominant air quality risk, is determined by the maximum of these sub-indices. Following that, the AQI is classified using the standard health impact ranges (Good, Satisfactory, Moderate, etc.). The structure of the input feature vector for crop prediction

X= [CPM2.5, CPM10, CNO2, CCO, CSO2, AQI] (3)
Where the derived AQI and the concentrations of the pollutants act as predictors. Table 1 explains the air quality indexing (AQI) ranges, categories, and their impact on crop growth.

AQI Range	Category	Description
0–50	Good	Ideal air conditions for all crops; very little danger to the roots and leaves
51–100	Satisfactory	Most crops can be grown there; however, sensitive types may require supervision.
101–200	Moderately polluted	decreased yield or growth in species that are susceptible; danger of physical stress
201–300	Poor	Noticeable effect on growth; some crops may exhibit decreased yield or discoloration.
301–400	Very Poor	Only extremely resilient crops are advised due to the high risk of root and leaf damage.
401–500	Severe	Inappropriate for the majority of crops; significant decline in yield and growth, signs of stress

A. Algorithm Steps:

B. Step 1- Data Preprocessing:

• Normalize Features To Have A Unit Variance And Zero Mean:
• Use interpolation or flagging to handle missing

pollutant values after data cleansing.

$$X_{\mathrm{norm}} = \frac{X - \mu}{\sigma} \quad (4)$$

where σ is each feature's standard deviation and μ is its mean.

C. Step 2- Aqi Computation:

• Determine the sub-index Ip for each pollutant (pp) among PM2.5, PM10, NO2, CO, and SO2 using breakpoint concentrations derived from the CPCB/US-EPA formula:

$$\mathrm{p} = \left(\frac{\mathrm{I_{Hi}} - \mathrm{I_{Lo}}}{\mathrm{BP_{Hi}} - \mathrm{BP_{Lo}}}\right)(\mathrm{Cp} - \mathrm{BP_{Lo}}) + \mathrm{I_{Lo}} \quad (5)$$

Where:
Cp is the measured pollutant concentration in parts per million; BPHi and BPLo are breakpoint concentrations that are slightly above and below Cp; and IHi and ILo are the corresponding AQI values for those breakpoints.

$AQI = \max_{p}\{I_p\}$ (6)

Step 3- Feature Vector Preparation:

• Compile the calculated AQI and pollutant concentrations into the input feature vector:

. The highest sub-index of all pollutants is the overall AQI:

$X=[C_{PM2.5}, C_{PM10}, C_{NO2}, C_{CO}, C_{SO2}, AQI]$ (7)

Step 4- Model Training:

• Use parameters to train a Random Forest Classifier on labelled data:

Nestimators=200, random_state=42 (8)

Step 5- Prediction:

• Use the trained Random Forest model to predict the appropriate crop for each new input feature vector X:

RF(X) (9)

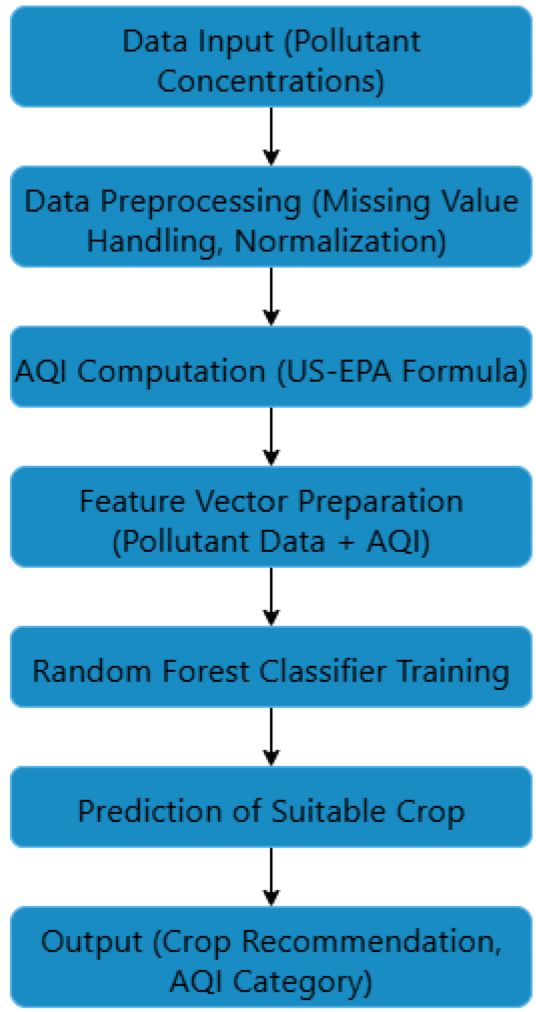
Step6- Output:

• Show the estimated crop recommendation, the corresponding AQI category (Good, Satisfactory, etc.), and the calculated AQI.

D. Data Sources:

- **Air Quality Data:** Multiple sources, including local environmental monitoring sensors, government public datasets (such as the Central Pollution Control Board [CPCB], India), and international repositories where appropriate, are used to obtain real-time local concentrations of pollutants PM2.5, PM10, NO2, CO, and SO2. IoT-based sensor networks placed in specific aeroponic farming locations or manual inputs can also be used to gather data.
- **Crop Data:** Crop labels were manually annotated using established scientific literature on crop tolerance thresholds associated with pollutant concentrations and Air Quality Index (AQI) values because integrated air quality and crop yield/suitability datasets were not available. This method creates a labelled dataset for model training by combining the most recent agronomic research with impact studies on air pollution.

- **Flow Chart:** Figure 3 explains the proposed methodology flowchart for air quality-driven crop prediction.

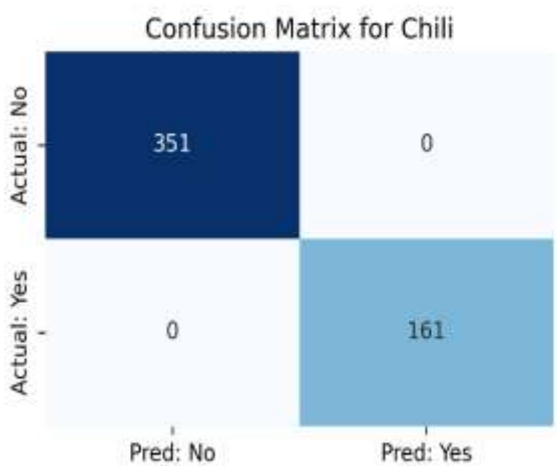


Proposed Methodology Flow chart (Fig. 3)

IV. RESULTS

Based on current concentrations of air pollutants and the associated Air Quality Index (AQI), the suggested methodology accurately forecasts the best crop for aeroponic farming. The findings show how well the suggested approach predicts the best crops for aeroponic farming in a range of air quality conditions by combining real-time air pollutant concentrations and the Air Quality Index (AQI) with a Random Forest classifier. Confusion matrices demonstrate perfect or nearly perfect classification performance, and the model exhibits high accuracy and robustness across a variety of crops, including rice, groundnuts, and chili. This suggests that the model's application of AQI-derived features and scientifically verified pollutant thresholds is very successful in capturing crop-specific air quality sensitivities, enabling dynamic, air quality-adaptive crop planning.

Furthermore, the equal significance of all pollutants under observation emphasizes the need for thorough air quality monitoring in order to maximize crop recommendations in soilless cultivation systems. These findings support the framework's potential for precision agriculture applications and operational deployment with the goal of improving sustainable urban farming. Fig 4 explains the confusion matrix for chili crop suitability prediction.



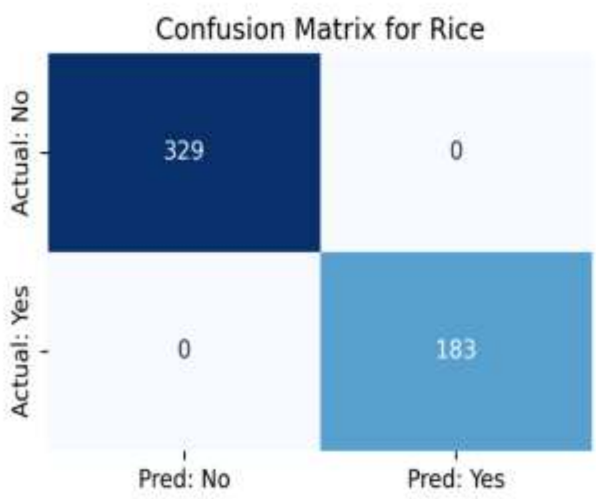
Confusion Matrix for Chili (Fig. 4)

Chili's confusion matrix displays the same pattern of results, with 161 positive and 351 negative cases correctly classified and zero misclassifications. This outcome shows how well-calibrated the Random Forest model is for determining the suitability of chili crops in a range of air quality conditions. The classifier's accuracy and the usefulness of utilizing AQI and particular pollutant features based on scientifically validated crop threshold data are both indicated by the perfectly diagonal confusion matrix. By guaranteeing that chili recommendations are both extremely dependable and sensitive to current environmental data, this supports the efficacy of the suggested methodology and qualifies the framework for operational deployment and future expansion. Fig 5 explains the confusion matrix for groundnut crop suitability prediction.

Confusion Matrix for Groundnut (Fig. 5)

Another important crop in the experimental setup is further assessed by the groundnut confusion matrix. With no incorrect classifications, the classifier accurately predicts 168 positive (suitable) and 344 negative (unsuitable) cases. The model's features and pollutant mappings are also very effective for groundnuts, as evidenced by this flawless classification (100% accuracy, sensitivity, and specificity).

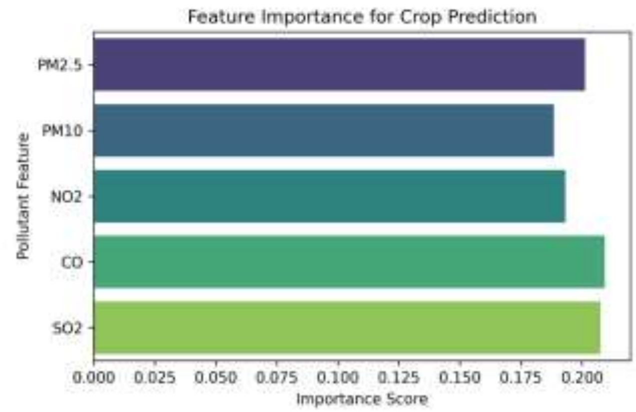
The lack of misclassifications indicates that, within the parameters of the test data, groundnut air quality sensitivities are robustly captured by pollutant-threshold-based labelling and AQI-driven feature engineering. The outcome demonstrates the model's applicability to precision agriculture in aeroponics, where pollutant levels have a direct impact on yield potential, and highlights the model's generalizability across various crop types. Fig 6 explains the confusion matrix for rice crop suitability prediction.



Confusion Matrix for Rice (Fig. 6)

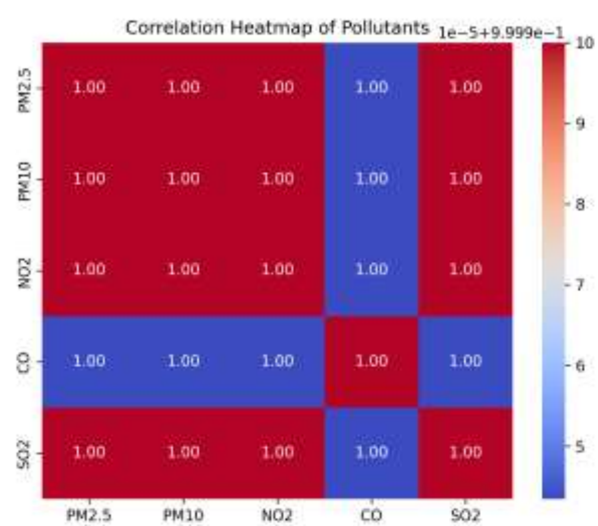
Based on real-time air quality and pollutant thresholds, the rice confusion matrix shows how well the suggested Random Forest classifier predicts whether rice is suitable for aeroponic farming. The findings show perfect classification: there were no false positives or false negatives, and all 183 positive cases where rice was appropriate and 329 negative cases where rice was not were correctly identified. For rice in the test dataset, this indicates 100% accuracy, sensitivity, and specificity.

The effectiveness of the air quality-driven methodology for rice recommendation is demonstrated by this high accuracy, which also confirms that the features derived from both AQI and individual pollutant concentrations are highly discriminative for this crop's tolerance criteria. These strong findings support the classifier's usefulness in facilitating dynamic, air quality-adaptive crop planning in soilless systems as well as the accuracy of pollutant threshold mapping. Fig 7 explains the feature importance plot highlighting key air pollutants for crop prediction.



Feature Importance for Crop Prediction (Fig. 7)

With PM2.5 being the most significant, the feature importance plot demonstrates that all monitored air pollutants PM2.5, PM10, NO2, CO, and SO2 make significant, nearly equal contributions to the Random Forest model's predictions of crop suitability in aeroponic farming. This balanced distribution emphasizes how crucial thorough monitoring of all these pollutants is for accurately determining crop tolerance and refining recommendations for soilless cultivation systems. Fig 8 explains the correlation heatmap of pollutants illustrating their interrelationships.



Correlation Heatmap of Pollutants (Fig. 8)

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V. CONCLUSION

A manually curated dataset maps AQI values and pollutant levels to crop suitability for crops like rice, chili, and groundnut. The model supports real-time data ingestion from sensors or public sources, making it scalable and adaptable across regions. Experimental results show reliable classification performance, with future improvements suggested by incorporating yield data and additional environmental factors like temperature and humidity. Overall, the framework enhances sustainable urban farming by optimizing air quality parameters like PM2.5, PM10, NO_2, CO, and SO_2. Reliable classification performance is shown by the experimental results; yield data and other environmental factors, such as temperature and humidity, are suggested for future improvements. All things considered, the framework improves crop yield, lessens the impact of pollution, and increases food security and climate resilience to support sustainable urban farming.

A. Future Scope:

• Gathering data on air quality and crop yield at the field level to fine-tune the model. • Adding more crop varieties and incorporating environmental data with multiple factors. • Creating intuitive user interfaces that provide predictive explanations to help farmers make decisions.

REFERENCES

1. T. Deshmukh, A. S. Rajawat and A. Potgantwar, "Machine Learning Technique for Crop Selection and Prediction of Crop Cultivation," 2023 International Conference on Advanced Computing Technologies and Applications (ICACTA), Mumbai, India, 2023, pp. 1-7, doi: 10.1109/ICACTA58201.2023.10392348.
2. S. Thirumal and R. Latha, "Automated Rice Crop Yield Prediction using Sine Cosine Algorithm with Weighted Regularized Extreme Learning Machine," 2023 7th International Conference on Intelligent Computing and Control Systems (ICICCS), Madurai, India, 2023, pp. 35-40, doi: 10.1109/ICICCS56967.2023.10142403.
3. K. Xiao, "Research on Crop Growth Detection and Prediction in Farmland Based on Agricultural Big Data," 2024 International Conference on Telecommunications and Power Electronics (TELEPE), Frankfurt, Germany, 2024, pp. 500-505, doi: 10.1109/TELEPE64216.2024.00095.
4. V. L. Narayana, S. Bhargavi, D. Srilakshmi, V. S. Annapurna and D. M. Akhila, "Enhancing Remote Sensing Object Detection with a Hybrid Densenet-LSTM Model," 2024 IEEE International Conference on Computing, Power and Communication Technologies (IC2PCT), Greater Noida, India, 2024, pp. 264-269, doi: 10.1109/IC2PCT60090.2024.10486394.
5. Narayana, V.L., Gopi, A.P., Patibandla, R.S.M. (2021). An Efficient Methodology for Avoiding Threats in Smart Homes with Low Power Consumption in IoT Environment Using Blockchain Technology. In: Choudhury, T., Khanna, A., Toe, T.T., Khurana, M., Gia Nhu, N. (eds) Blockchain Applications in IoT Ecosystem. EAI/Springer Innovations in Communication and Computing. Springer, Cham. https://doi.org/10.1007/978-3-030-65691-1_16
6. V. Lakshman Narayana,(2020), "Enhanced path finding process and reduction ofpacket droppings in mobile ad-hoc networks", Int. J. Wireless and Mobile Computing, Vol. 18, No. 4, 2020, pp-391-397.
7. Narayana, V.L., Gopi, A.P., Patibandla, R.S.M. (2021). An Efficient Methodology for Avoiding Threats in Smart Homes with Low Power Consumption in IoT Environment Using Blockchain Technology. In: Choudhury, T., Khanna, A., Toe, T.T., Khurana, M., Gia Nhu, N. (eds) Blockchain Applications in IoT

Ecosystem. EAI/Springer Innovations in Communication and Computing. Springer, Cham. https://doi.org/10.1007/978-3-030-65691-1_16

8. Chaitanya, K., and S. Venkateswarlu. "DETECTION OF BLACKHOLE & GREYHOLE ATTACKS IN MANETs BASED ON ACKNOWLEDGEMENT BASED APPROACH." Journal of Theoretical & Applied Information Technology 89.1 (2016).
9. Lakshman Narayana, V., Rao, G.S., Gopi, A.P., Lakshmi Patibandla, R.S.M. (2022). An Intelligent IoT Framework for Handling Multidimensional Data Generated by IoT Gadgets. In: Al-Turjman, F., Nayyar, A. (eds) Machine Learning for Critical Internet of Medical Things. Springer, Cham. https://doi.org/10.1007/978-3-030-80928-7_9
10. Narayana, V. L., et al. "Computer Tomography Image Based Interconnected Antecedence Clustering Model Using Deep Convolution Neural Network for Prediction of COVID-19." Traitement du Signal, vol. 40, no. 4, 2023, pp. 1689–1696. https://doi.org/10.17762/ijritcc.v11i9s.73
11. Sujatha, V., Vasumathi Devi Majety, Satya Sandeep Kanumalli, and V. S. Sai Rama Krishna Komanduri. "Brain Tumour Detection Using Auto-Encoder and Multi-Layer Perception." AIP Conference Proceedings, vol. 2724, no. 1, AIP Publishing, 28 Apr. 2023. https://doi.org/10.1063/5.0130160
12. Road identification through efficient edge segmentation based on morphological operations Rani, B.M.S., Majety, V.D., Pittala, C.S., ... Sandeep, K.S., Kiran, S. Traitement du Signal, 2021, 38(5), pp. 1503–1508
13. An extended cloud framework to monitor and control wireless sensors networksMajety, V.D., Sravanthi, G.L., Didla, D. International Journal of Innovative Technology and Exploring Engineering, 2019, 8(11), pp. 3805–3808
14. V. Pavani, N. VijayaLakshmi, N. Harika, G. S. Sowjanya and V. Deepthi, "Deep Learning-based Analysis of Brain MRI for Enhanced Diagnosis of Multiple Sclerosis," 2024 5th International Conference on Data Intelligence and Cognitive Informatics (ICDICI), Tirunelveli, India, 2024, pp. 1141-1148, doi: 10.1109/ICDICI62993.2024.10810928.
15. Kumari, G. R. P., Reddy, A. H., Lakshmi, K., Abhinaya, B., Sanjana, S., & Naresh, A. (2024, March). Time-Frame-Based Drowsiness Detection System Using CNN. In 2024 2nd International Conference on Disruptive Technologies (ICDT) (pp. 711-716). IEEE.
16. Sirisha, Aswadhati, B. Siva Jyothi, and P. Sandhya Krishna. "Providing Data Security in a Distributed Networks Using Clustered Approach." International Journal of Advanced Science and Technology 28, no. 16 (2019): 1907-1915.
17. Arumugham, V., Sankaralingam, B. P., Jayachandran, U. M., Krishna, K. V. S. S. R., Sundarraj, S., & Mohammed, M. (2023). An explainable deep learning model for prediction of early-stage chronic kidney disease. Computational Intelligence, 39(6), 1022-1038.
18. Rayachoti, Eswaraiah, Sudhir Tirumalasetty, and Silpa Chaitanya Prathipati. "Watermarking system for telemedicine based on FABEMD." Multimedia Tools and Applications 81.30 (2022): 44383-44404.
19. V. K, S. G, R. P. P and R. M, "Enhancing Predictive Accuracy for Agricultural Crop Yields in Indian States Using Power Transformation in Machine Learning Models," 2024 10th International Conference on Advanced Computing and Communication Systems (ICACCS), Coimbatore, India, 2024, pp. 2403-2408, doi: 10.1109/ICACCS60874.2024.10716829.
20. R. J, V. K. G. Kalaiselvi, A. Sheela, D. S. D and J. G, "Crop Yield Prediction Using Machine Learning Algorithm," 2021 4th International Conference on Computing and Communications Technologies (ICCCT), Chennai, India, 2021, pp. 611-616, doi: 10.1109/ICCCT53315.2021.9711853.
21. Kavishwar, S., & Uppal, S. K. (2020). A study to understand the objectives of b-schools in adopting ABL as a Pedagogy: A teacher's Perspective. Sambodhi. 43(04), 180-185.
22. Kavishwar, S (2024). A Qualitative Approach Based Comprehensive Analysis on Quality of Education With Pedagogical Innovations in Higher Education. International Journal of Computational and

Experimental Science in In Engineering, 10(4), 1814-1823.
23. Joshi, M., Kothari, P. and Kavishwar, S. (2024). A Study on Determinants of Profitability in Indian Banks. Journal of Informatics Education and Research. 4(3), 22-26.
24. Kavishwar, S. (2024). A Theoretical Framework Analyzing Impact of Embedding Entrepreneurial Skills in Education on Economical Growth. Journal of Lifestyle and SDGs Review, 4(4), e03550.
25. Kotadiya U, Arora AS, Yachamaneni T. Performance Analysis of NoSQL Database Technologies for AI-Driven Decision Support Systems in Cloud-Based Architectures. IJERET [Internet]. 2022 Jun. 30 [cited 2026 Apr. 5];3(2):60-9.
26. Yachamaneni T, Kotadiya U, Arora AS. Evaluating the Efficacy of Machine Learning Algorithms in Credit Card Limit Optimization and Customer Segmentation. IJETCSIT [Internet]. 2022 Oct. 30 [cited 2026 Apr. 5];3(3):51-6.
27. Janumpally, Bharath Kumar Reddy. (2026). Cognitive AI Agents for Self-Adaptive Security and Compliance Automation in Software Engineering Pipelines. 10.1109/ICAUC68182.2026.11441048.
28. Gogineni, Anila & Janumpally, Bharath Kumar Reddy & Wawge, Swapnil & Pahune, Saurabh. (2025). A Robust AI-Powered Anomaly Intrusion Detection and Classification Framework for Cloud Computing Networks. 1-6. 10.1109/INDISCON66021.2025.11253743.
29. Tummuri, S. S. R. (2022). Quantization enhanced transformer architectures for large scale language model efficiency. International Journal of Scientific Research in Computer Science, Engineering and Information Technology, 8(3), 891–904.
30. Tummuri, S. S. R. (2022). Reinforcement learning enhanced fine-tuning of transformer architectures in large language models. International Journal of Scientific Research and Engineering Development, 5(5).
31. A. Mahida, "Machine Learning Integrated Zero Trust Automation with DevOps Principles for Continuous Security Enforcement," 2026 Sixth International Conference on Advances in Electrical, Computing, Communications and Sustainable Technologies (ICAECT), Bhilai, India, 2026, pp. 1-7, doi: 10.1109/ICAECT68478.2026.11426026.
32. Ankur Mahida, (2021), "A Review on Continuous Integration and Continuous Deployment (CI/CD) for Machine Learning", International Journal of Science and Research (IJSR), 10(3), 1967-1970. https://dx.doi.org/10.21275/SR24314131827, https://www.ijsr.net/getabstract.php?paperid=SR24314131827
33. Jonnalagadda, P.K. (2026). Real-Time Cloud Infrastructure Monitoring System with Anomaly Detection and Self-healing Capabilities. In: Kumar, V.N., Senkerik, R., Prasad, V.K., Kumar, T.K. (eds) Intelligent Computing and Communication. ICICC 2025. Lecture Notes in Networks and Systems, vol 1839. Springer, Cham. https://doi.org/10.1007/978-3-032-18349-1_43
34. Jonnalagadda, Pawan Kalyan. "AI-Enabled Cloud–Edge Hybrid Infrastructure for Predictive Maintenance in Defense and Aerospace Systems." International Journal of Science, Engineering and Technology, vol. 12, no. 2, 2024.
35. Veginati, Navya. "Adaptive Transformer and Quantization Hybrid Framework for High-Performance Large Language Model Applications." United International Journal of Engineering and Sciences, vol. 5, no. 4, Dec. 2025, pp. 46–56
36. Veginati, Navya. "Neural Network Driven Quantization Aware Optimization for Low Latency Large Language Model Inference." International Journal of Scientific Research in Computer Science, Engineering and Information Technology, vol. 10, no. 3, May-June 2024, pp. 1162–1170, doi:10.32628/CSEIT25113584.
37. Racha, Ganesh. "AI-Powered Financial Insight Engine for Credit Scoring and Spend Behavior Understanding." International Journal of Scientific Research & Engineering Trends, vol. 10, no. 2, Mar.–Apr. 2024, pp. 1–8.
38. Racha, Ganesh. "Adaptive Quantum Blockchain for Secure IoT Resource Coordination." International Journal of Science, Engineering and Technology, vol. 11, no. 3, 2023.

39. Nijim, M., Albataineh, H., Kanumuri, V., Goyal, A., Mishra, A., Hicks, D. (2023). Countering Cybersecurity Threats in Smart Grid Systems Using Machine Learning. In: Daimi, K., Alsadoon, A., Peoples, C., El Madhoun, N. (eds) Emerging Trends in Cybersecurity Applications. Springer, Cham. https://doi.org/10.1007/978-3-031-09640-2_14
40. Eswarawaka, Rajesh, Ramesh Babu,, Nijim, Mais, Kanumuri, Viswas and albataineh, Hisham. "Effectiveness of machine learning and deep learning in cybersecurity". Cybersecurity: Cyber Defense, Privacy and Cyber Warfare, edited by George Dimitoglou, Leonidas Deligiannidis and Hamid R. Arabnia, De Gruyter, 2025, pp. 199-214. https://doi.org/10.1515/9783111436548-009
41. Jingar, N. K. (2022). Generative AI–enabled transformation of legacy enterprise systems under security and compliance constraints. International Journal of Scientific Research in Computer Science, Engineering and Information Technology, 8(2), 760–770. https://doi.org/10.32628/CSEIT23906219
42. Nirmal Kumar Jingar. (2021). Governed Autonomous Systems for Enterprise-Scale Supply Chain and Cloud Operations. In International Journal of Science, Engineering and Technology (Vol. 9, Number 6). Zenodo. https://doi.org/10.5281/zenodo.18629297