

Advancing Food Production Efficiency and Waste Reduction in Smart Cities Using Machine Learning

Shujaat Ali Rathore	Department Computer Science & Information Technology, University of Kotli, Azad Jammu and Kashmir shujaat.ali@uokajk.edu.pk
Muhammad Hammad u Salam	Department Computer Science & Information Technology, University of Kotli, Azad Jammu and Kashmir
Qamar Muhay-ud-din	Department Computer Science & Information Technology, University of Kotli, Azad Jammu and Kashmir
Muhammad Irfan	National College of Business Administration & Economics, Multan Campus, 60000, Pakistan
Sidra Zulfiqar	Department of Computer of Science, Okara University, Okara, 56300, Pakistan

Abstract: *The growth of cities is a challenge for sustaining food systems, as there is a limited supply of resources to support these systems. This paper seeks to understand the impact of IoT and Machine Learning (ML) on the production systems of smart cities through agriculture waste and resource consumption reduction strategies. An IoT equipped urban agriculture system that incorporates machine learning (ML) can optimize resource use, forecast crop yield and reduce food losses at every stage of the production and supply chain. This study offers a water-saving irrigation system, soil health diagnostics, and predictive crop yield reporting to illustrate how these technologies can facilitate agriculture system productivity. This paper outlines the issues associated with data aggregation and model building, including privacy and control of the information, identifies gaps, and makes suggestions for further curriculum and system building. Smart cities with the help of proper datasets, policies, algorithms, and models, will averts the negative consequences of urban agriculture. The framework presented in this paper emphasizes that environmentally sustainable agriculture in cities offers the ability to simultaneously resolve a plethora of problems related to the smart city solutions.*

Keywords: Machine Learning, Smart Cities, Sustainable Agriculture, Precision Farming, IoT in Agriculture, Food Production Efficiency, Waste Reduction, Predictive Analytics, Resource Optimization, Urban Food Systems

1. Introduction

With the passage of time urbanization all over the world is on the rise, cities are now struggling to meet the demands of food and also consider environmental sustainability. There is a strain on urban food systems because of insufficient agriculture land, resource mismanage, and the constant risk of environmental deterioration. Conventional agricultural practices, which are relatively resource-intensive and prone to waste, cannot be integrated into the advanced framework of smart cities. The integration of new technologies such as machine learning (ML) and the Internet of Things (IoT) serve to create novel opportunities for urban ecologies by providing sustainable food production and waste minimization solutions [1].

Agriculture has started to adopt machine learning and IoT technologies, which go beyond traditional farming practices to include forecasting, optimizing resources, and monitoring both crops and the environment in real time. Both soil, weather, and smart irrigation sensors form an IoT network that cultivates real-time information that machine learning algorithms can parse and analyze to provide actionable solutions to improve resource efficiency, yield forecasting, and food waste reduction across the supply chain [2], [3]. In particular, with precision agriculture ML systems, stress caused by surrounding environment, pest activity, and diseases can be mitigated by early detection and risk-forecasting techniques [4].

Smart cities focus on digital infrastructure development which creates the perfect environment for implementing ML and IoT solutions for urban agriculture. In contrast to rural farms, urban agriculture pursuits are typically bound by spatial limitations, and therefore have a need for a highly productive system to satisfy the needs. The ability to optimize water and nutrient supply, track crop and environmental health in real time, and check various growth conditions can dramatically improve productivity and sustainability [5], [6]. Moreover, the combination of the urban agricultural systems with the smart waste management systems can guarantee that food waste is reduced by highlighting inefficiencies in production, distribution, and consumption [7].

Finding ways to increase food production without further degrading the environment is one of the goals of sustainable development and promotes the use of water, energy, and land resources in more productive ways. Addressing these challenges is Precision agriculture which ML models facilitate by diagnosing conditions in real-time and strategically distributing the required amount of fertilizers, water, and energy [8]. Moreover, the pattern recognition and trend analysis capabilities of ML allow for resource-saving solutions that would not be possible with traditional approaches because of the immense size of the datasets being examined [9], [10]. For example, agricultural activities such as irrigation can be automated needs further ML intervention to minimize water usage, through the application of Smart irrigation systems, water is supplied at the most optimal time and place [11].

Even with the tremendous promise these technologies hold, implementing them continues to remain a challenge. Deficiencies like amalgamation of data, model enlargement, and the security threats from the IoT devices remain crucial barriers to mass acceptance. Moreover, the adoption of IoT systems in data analysis is dwarfed by the exorbitantly priced initiation rollouts and the expense of training personnel alongside is equally high, especially in resource drained urban settings. Still, the expansion of ML open source framework alongside the fall in IoT device pricing helps to overcome barriers and increase the adoption of sustainable agricultural practices in urban regions.

This document investigates the use of ML and IoT technology in promoting urban sustainable agriculture in smart cities, specifically on increasing the efficiency of food production and reducing the agro-waste. While studying precision agriculture employing IoT systems at services automation, researchers have provided a literature review in essay 2. In these sections, we propose the application of integrated systems of urban agriculture control and field basic agriculture. In these, we enumerate issues and offer solutions. They then give business-like examples of places which have adopted the model as supported cases. After that, we outline the most important results and advice for further studies in the last sections.

2. Literature Review

ML and IoT are revolutionizing food production in smart cities by improving resource management and curbing waste. The research done on real-time, precision agriculture demonstrates the feasibility of making informed decisions using ML-based models that analyze enormous amounts of data collected via IoT sensors in real time. These technological advancements help to mitigate the space, water, and other resource challenges that exist in metropolitan regions.

2.1 Precision Agriculture and Predictive Analytics

Sensors based on IoT technology, paired with agricultural ML models, provide the ability to monitor soil, crops, and other environment parameters in real-time, which are a backbone for precision agriculture [16]. Implementation of these technologies has been shown to result in optimization of irrigation cycles, increase in nutrient transfer efficiencies, and yield prediction accuracy. Decision trees and support vector machines in ML, for instance, provide farmers with powerful insights into the efficient use of available water, fertilizer, and labor resources [17], [18]. For example, ML enabled smart irrigation systems that deliver water only when and where it is needed achieve water savings of 30% without any impact on crops [19].

2.2 IoT-Driven Waste Reduction

The proper use of IoT devices reduces waste by allowing for real-time monitoring of food [20]. Urban farming has smart waste management systems that pinpoint the gaps in the food supply chain from production to consumption [21]. They estimate loss rates over time, help maintain ideal conditions for storage, actively monitoring so that, as a result, so as to conserve food resources post-harvest. Multiple case studies show that IoT systems for waste tracking can lower food waste in metropolitan areas by 40% [22].

2.3 Integration of ML and IoT in Urban Agriculture

ML and IoT have their specific applications in urban agriculture which Grows as a result of these enabling modern technologies. IoT sensors continuously gather humidity, temperature, and soil moisture and processes these variables using ML to estimate crop yield and allocation of resources [23]. In addition to that, machine learning technologies like neural networks and reinforcement learning improve yield forecasts by taking into account the past and present data simultaneously [24].

2.4 Environmental Sustainability and Resource Optimization

ML-driven precision agriculture contributes towards sustainable development through efficient resource allocation, conserving both water and power. Smart cities that have incorporated such technologies have confirmed improved crop yields with lower water usage and minimum emissions of greenhouse gases [25]. Environmentally predictive ML-based management of fertilization prevents soil degradation and minimization of environmental impact [26]. A combination of agriculture and urbanization through dutch experts aids farmers in reaching sustainable production goals without hindering future cultivation potential growth [27].

2.5 Challenges and Solutions

Issues surrounding data integration, model scalability, and privacy still exist despite the apparent benefits. Seamless integration of IoT devices with cloud services and ML models poses a great challenge [28]. The problem of scale comes when the ML models developed for small scale are implemented in large urban farms [29]. Researchers recommend modular IoT architectures, decentralized computing, and open ML frame works to help with these challenges [30].

The combination of nutrient delivery systems with reinforcement learning models enables targeted application of fertilizers and mitigates excess usage and its associated harms per citation 19. In addition, analytics has made it possible to track and optimize different facets of the food supply chain in real time, which has significantly reduced post-harvest losses and waste as noted in [20] and [21]. Nonetheless, issues regarding data integration and scalability emphasize the requirement for modular IoT architectures and efficient data-sharing policies for large scale deployment [29].

The Table.1 contains all relevant contributions and findings of the world that merged ML and IoT with agriculture and its waste within the smart city paradigm. Particularly forefront are the precision agriculture systems that utilize ML models such as decision trees and neural network, which significantly improve resource allocation and crop yields while wasting less water [16], [17]. The IoT-

enabled waste management systems also diminish waste and improve food quantity and quality in storage [18].

Table 1: Comparative Analysis of Key Studies on ML and IoT in Food Production

Reference	Key Focus	ML Technique Used	IoT Application	Main Contribution	Impact
[16]	Precision agriculture	Decision trees, SVM	Soil and moisture sensors	Optimized resource allocation	Increased crop yield by 20%
[17]	Predictive irrigation	Neural networks	Smart irrigation systems	Reduced water consumption	Water savings of up to 30%
[18]	Waste reduction	Predictive analytics	Cold storage tracking	Improved food storage efficiency	Reduced spoilage by 40%
[19]	Nutrient optimization	Reinforcement learning	Nutrient delivery systems	Enhanced nutrient application precision	Reduced fertilizer use by 25%
[20]	Resource optimization	Clustering, regression	Environmental monitoring	Data-driven yield forecasting	Resource savings of 15%
[21]	Waste management integration	Logistic regression	Supply chain monitoring	Minimized post-harvest food waste	Reduced food waste by 35%
[22]	Sustainability assessments	Bayesian models	Air and water quality sensors	Sustainable resource management	Improved environmental quality

In general, the reviewed studies provide evidence that the fusion of ML and IoT technologies improves food industries and simultaneously reduces the carbon footprint, which is essential for sustainable agriculture in urban areas.

3. Proposed Framework for ML-Driven Sustainable Agriculture

This framework seeks to merge machine learning ML processes with IoT enabled technologies for smart cities to increase efficiency in food production while minimizing resources consumption and waste. The system comprises three pillars: a data acquisition layer, a predictive modeling layer, and a decision support system DSS. These components together aim at optimizing the consumption of water, improving yield prediction, and decreasing food waste, thus enhancing sustainable practices of urban agriculture.

3.1 Data Acquisition and Integration

The collection of real-time data as the first step is facilitated by a network of IoT sensors distributed around the urban agricultural sites that are monitored by crop production managers. The sensors capture the essential parameters like moisture content in the soil, the temperature, the levels of nutrients, and health of the crops. Moreover, the weather monitoring stations collect data on humidity, rainfall, and air quality. This step acting as the base layer feeds a great amount of accurate information into the predictive models, which proficiently enhance the modeling processes.

The input from IoT sensors link to the ‘acquisition of data’ section, which later links to the predictive modeling section of the framework. This section triumphantly captures the major outputs, which are the prediction of yield, optimization of water usage, and reduction of waste. The decision support system processes these outputs to provide higher level solutions which enable faster and smarter decision making for the farmers and better integration with the waste management systems.

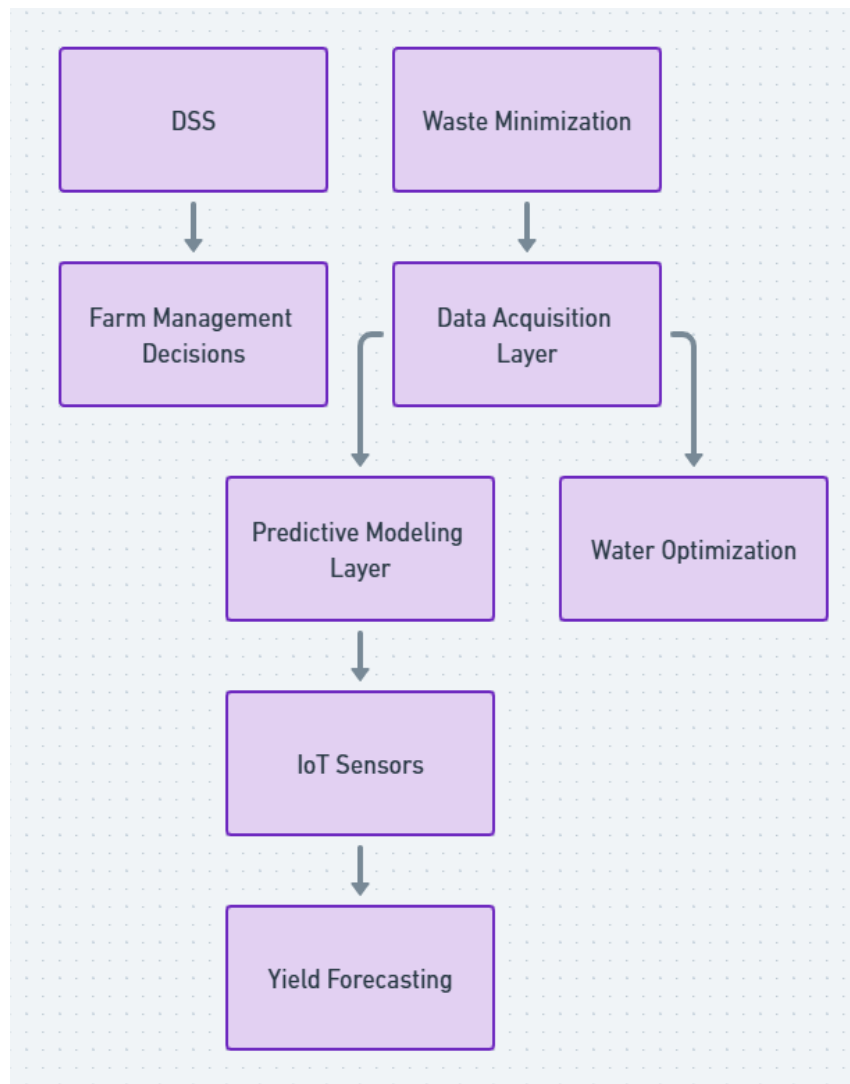


Figure 1: Proposed ML-Driven Framework for Sustainable Agriculture

The diagram illustrates an integrated network of data acquisition and predictive modeling that enhances farm management practices. It commences with Waste Management Integration, which feeds into a Decision Support System (DSS) that impacts Farm Management Strategies. At the same time, Waste Minimization supports a Data Acquisition Layer, which collects information for a Predictive Modeling Layer connected to IoT Sensors. These sensors scout Mid and Late Season Yield Forecasting and enable Water Optimization so that resources are not squandered on agricultural activities.

3.2 Predictive Modeling and Decision Support

The layer enables insights to be actionable through a collection of data from multiple sources or campaigns including Decision Support Systems using machine learning models. This layer is responsible for:

Enhanced Yield Forecasting: Machine learning techniques utilize real-time and historical data to formulate everchanging crop yield predictions during different conditions.

Water Usage Optimization: Proactive models based smart irrigation systems allocate the water resource towards crop needs and environmental factors, edging economical water utilization.

Resource Wastage Minimization: Predictive models by scrutinizing phenomena concerning an organism's growth patterns and variance spotting can forewarn of potential sources of resource wasting faster than others.

This data is incorporated into the DSS system that contains interactive dashboards for users to monitor the performance of crops, the consumption of resources, and the level of waste produced. Farmers and urban agriculture managers receive recommendations in real time, enabling better decisions that reduce the amount of resources spent.

3.3 Waste Management Integration

An urban waste management system is one of the most critical components of the circular economy that the framework is developed upon. As demonstrated in Figure 2, IoT-enabled waste sensors detect the production of organic waste and relay the information to an analytical module. The system suggests composting and nutrient recovering processes for organic materials based on the automated analysis of the waste.

Composting and nutrient recovery approaches tend to increase the quality of processed waste while converting it into compost and/or nutrients. Such an analysis of the waste aids a waste management structure on IoT wastes sensors. The nutrients extracted can then be reused, thereby preventing the depletion of resources.

The Integration diagram of waste management describes an efficient, organic waste treatment approach using IoT and analytics. The waste IoT sensors start the process by initiating the collection of waste data, which is analyzed in a Data Analysis Module. This module provides suggestions for Nutrient Recovery and Composting, both of which facilitate Waste Processing. The process of Waste Processing then proceeds to the stage of producing Recycled Organic Waste, which contributes to responsible waste processing. Collectively, these components make up a data-centric green agricultural system. This not only inhibits the amount of organic waste that is produced, but also increases the amount of waste that can be put back into use, making agriculture more efficient and sustainable.

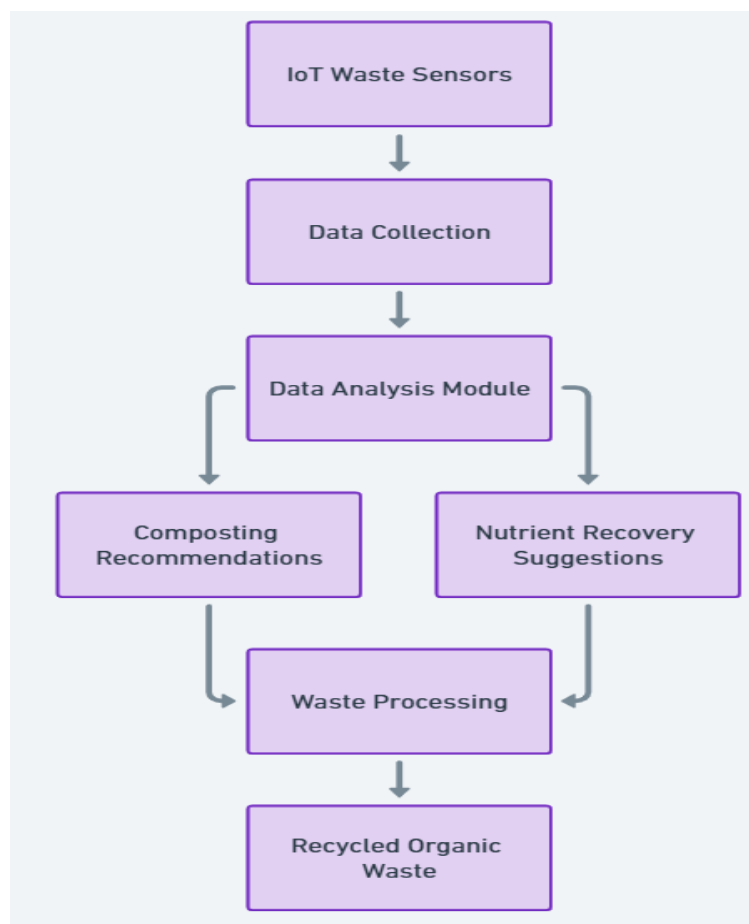


Figure 2: Waste Management Integration within the Framework

3.4 Benefits and Outcomes

The framework proposed in this paper has the following benefits:

Cost reduction: Monitoring and modeling in real time allows water, nutrients, and labor to be effectively utilized, saving resources.

Higher productivity: Stress factors can be identified early on, along with predictive yield forecasts, providing a higher value of crop yield.

Green waste: Multi-systems integration with compost and refuse systems improves the urban architecture of agriculture by cutting down on waste generated.

And most importantly, this framework solves the issue of food sustenance through an all encompassing, data driven strategy for smart cities, maintaining maximum environmental sustainability and food availability.

4. Challenges and Solutions

4.1 Data Integration and Interoperability

Integrating various sources of data is a major challenge when using machine learning (ML) and IoT technologies for sustainable agriculture. Urban agriculture involves many different IoT devices, weather stations, and environmental sensors that collect data in different formats [31]. These systems need a seamless interoperability approach with unified data schemes, which makes a multitude of issues. Inefficient data exchanges can slow down processing speeds, increasing the chances of inaccurate estimates for yield and resource management [32].

As a solution, the use of distributed data lake architecture that enables the efficient processing of agricultural data is suggested [21]. In addition, integrating cloud storage together with edge servers mitigates the lag in real-time monitoring and decision-making processes [23]. Finally, federated learning allows agricultural sites to train ML models collaboratively with impersonalized data from different places without model degradation [19].

4.2 Privacy and Security Concerns in IoT-Based Agriculture

The application of IoT in agriculture raises the potential for cyber attacks like data breaches, stealing information, or unauthorized access which can tamper with the systems [33]. Since ML models make decisions based on real-time IoT data, erroneous predictions could be made in food production, resource allocation, and overall operational optimum efficiency [34].

To help combat these issues, it's crucial to put active preventive measures into action. AI facilitated anomaly detection systems can track IoT networks for unusual activities, associating certain patterns with breaches or potential threats [35]. The implementation of blockchain technology in IoT-based agriculture systems increases data security due to decentralized validation and immutable records of transactions, [36] while AI-assisted fraud prevention alters the decision of the machine learning predictive and protective system without permission to change the authorization settings [37].

4.3 Scalability and Adaptability of ML Models in Diverse Environments

IoT-enabled farms in urban areas usually face multiple sustainable development goals like rapidly changing climatic conditions, variable quality of soil, and efficiently limited space for food production [38]. These standard ML models which are trained on basic datasets have limited scope for mobility and lack optimization in the actuality when applied to different areas geologically-wise [39].

Transfer learning methods help solve this problem, as ML models with previously trained models do not need retraining. Furthermore, reinforcement learning methods help ML systems to self-adjust farming policies based on changing climates. [23] The use of deep learning together with a rule-based

system increases the hybrid AI model's interpretability and agricultural automation compliance with environmental constraints.

In conclusion, the versatility of IoT and ML can drastically revolutionize agriculture, but risks concerning data integration, security, and model possibility certainly need to be triaged first. Implementation of sophisticated AI frameworks, renovation of data management systems, and cyber security measures would meet the urban food production system's demands, which includes efficiency, security, and flexibility.

5. Discussion

The amalgamation of machine learning and IoT technologies into urban agriculture has the potential to improve food production and reduce waste. However, there are hurdles for the effective and wide-reaching use of these innovations: data integration and interoperability problems, lack of adequate privacy and security measures, and the feasibility of incorporating ML in various agricultural settings.

Data integration and interoperability are significant challenges considering the different forms of data deriving from IoT-enabled sensors, environmental monitoring systems, and agricultural machinery. The inefficiencies in data processes and resource allocation are often rampantly found due to the absence of standardized data formats and uniform communicational protocol systems. As a solution towards scaling these barriers, data lakes architecture and federated learning systems offer the ability to exchange vast amounts of data with privacy. Furthermore, edge computing lowers the latency while increasing the efficiency of real time decision making for urban farmers, constantly allowing them to make adjustments to changing farming conditions in real-time.

Another challenge to the adoption of IoT-based agriculture is the privacy and security risks that stem from them. The tremendous amount of data gathered through IoT, such as soil conditions, weather data, and crop health indicators may serve as resources for cyber-attacks. Data like these, if accessed without permission, can create predictive analytics that lead to manipulative econometric results, and thus severe losses economically. To overcome these issues, blockchain technology with advanced encryption authentication and distributed data storage can be adopted. AI powered anomaly detection augments the best results by providing complete transparency against the potential threat of cyber attacks in real time.

The diversity of climate, soil type, and resources in an area has posed a challenge in the scalability and flexibility of machine learning models for urban farming. Ordinary ML models, with their deeply trained and highly specialized sets of data, tend to face greater difficulties when multicross farming settings, hence subsequently increasing their ineffectiveness. A potential remedy to this is choosing local datasets and using them to fine-tune pre trained models. Moreover, allocating resources through dynamically adjustable strategies based on real life environmental feedback is what has been achieved through using reinforcement learning. Urban farmers now have the capability to implement, without necessitating much computational power, crop farming solutions that can adapt to site specific conditions through cloud ML tools.

The integration of the Internet of Things and machine learning, paired with aromatherapy has a broad spectrum of challenges, but showing clear promise through the improvement of resource productivity, food waste, and maintenance of sustainable farming practices. The implementation of smart irrigation pairs, automated yield watching, and waste management systems prove to be beneficial by optimizing water, increasing crop yield productivity, and reducing losses after harvest. There is an expectation that future culinary systems with the incorporation of AI will become more resilient and efficient, though such farming systems will be necessary to tackle in urban locations.

Since smart cities are emerging, the function of intelligent agricultural systems must be essential for the provision of food sustainability to urban areas. Constructing holistic frameworks that deal with the

current gaps for optimum utilization of ML and IoT-enabled agriculture services can be done through the collaboration of researchers, decision-makers, and technologists.

6. Conclusion

The application of machine learning (ML) and the Internet of Things (IoT) within the context of urban agriculture has great potential to increase productivity and minimize wastes. Systems using IoT sensors can be utilized to gather data which ML systems can analyze in real-time to enhance resource management, predict yields, and lessen environmental burdens. However, problems such as privacy issues, data integration, and model scalability are barriers toward successful implementation and must be solved first.

The gaps these problems present can be filled by implementing enhanced cybersecurity measures, standardized data sharing techniques, and adaptable ML algorithms for various urban agriculture settings. In addition, cloud based platforms and edge computing architecture enable distributed intelligent agriculture systems and foster real time agriculture decision-making. Risks from unauthorized access and cyber-attacks can be managed with the help of blockchain technology for secure information building.

Even with these challenges, the use of ML and IoT in the context of urban agriculture has significantly enhanced sustainable practices, resource management, and food security. Reduction of water usage, crop productivity, and food wastage along the supply chain have all benefited from smart irrigation devices, autonomous waste controllers, and AI powered analytics systems.

In order to build upon these technologies, the integration of different practices, be it from a research background, policymaking, or even technology designing, is essential for urban farmers. More efforts should be put towards developing affordable IoT for miniature urban farms along with AI powered decision facilitating systems and federated learning applications.

Sustainable and smart cities which are able to meet the global challenges of food safety and environmental issues will benefit greatly with solving existing challenges and advancing IoT and ML powered agriculture technology.

References

- T. M. Ghazal et al., "Fuzzy-Based Weighted Federated Machine Learning Approach for Sustainable Energy Management with IoE Integration," 2024 Systems and Information Engineering Design Symposium (SIEDS), Charlottesville, VA, USA, 2024, pp. 112-117, doi: 10.1109/SIEDS61124.2024.10534747.
- J. I, T. A. Khan, S. Zulfiqar and M. Q. Usman, "An Architecture of MySQL Storage Engines to Increase the Resource Utilization," 2022 International Balkan Conference on Communications and Networking (BalkanCom), Sarajevo, Bosnia and Herzegovina, 2022, pp. 68-72, doi: 10.1109/BalkanCom55633.2022.9900616.
- Suri Babu Nuthalapati and Aravind Nuthalapati, "Transforming Healthcare Delivery via IoT-Driven Big Data Analytics in a Cloud-Based Platform," J. Pop. Ther. Clin. Pharm., vol. 31, no. 6, pp. 2559-2569, Jun. 2024, doi:10.53555/jptcp.v31i6.6975.
- T. A. Khan, M. S. Khan, S. Abbas, J. I. Janjua, S. S. Muhammad and M. Asif, "Topology-Aware Load Balancing in Datacenter Networks," 2021 IEEE Asia Pacific Conference on Wireless and Mobile (APWiMob), Bandung, Indonesia, 2021, pp. 220-225, doi: 10.1109/APWiMob51111.2021.9435218.
- S. Nuthalapati and A. Nuthalapati, "Advanced Techniques for Distributing and Timing Artificial Intelligence Based Heavy Tasks in Cloud Ecosystems," J. Pop. Ther. Clin. Pharm., vol. 31, no. 1, pp. 2908-2925, Jan. 2024, doi:10.53555/jptcp.v31i1.6977.

- J. I. Janjua, S. Kousar, A. Khan, A. Ihsan, T. Abbas and A. Q. Saeed, "Enhancing Scalability in Reinforcement Learning for Open Spaces," 2024 International Conference on Decision Aid Sciences and Applications (DASA), Manama, Bahrain, 2024, pp. 1-8, doi: 10.1109/DASA63652.2024.10836237.
- Aravind Nuthalapati, "Smart Fraud Detection Leveraging Machine Learning For Credit Card Security," Educational Administration: Theory and Practice, vol. 29, no. 2, pp. 433-443, 2023, doi:10.53555/kuey.v29i2.6907.
- J. I T. M. Ghazal, W. Abushiba and S. Abbas, "Optimizing Patient Outcomes with AI and Predictive Analytics in Healthcare," 2024 IEEE 65th International Scientific Conference on Power and Electrical Engineering of Riga Technical University (RTUCON), Riga, Latvia, 2024, pp. 1-6, doi: 10.1109/RTUCON62997.2024.10830874.
- Suri Babu Nuthalapati, "AI-Enhanced Detection and Mitigation of Cybersecurity Threats in Digital Banking," Educational Administration: Theory and Practice, vol. 29, no. 1, pp. 357-368, 2023, doi: 10.53555/kuey.v29i1.6908.
- J. I. Janjua, M. Nadeem, Z. A. Khan and T. A. Khan, "Computational Intelligence Driven Prognostics for Remaining Service Life of Power Equipment," 2022 IEEE Technology and Engineering Management Conference (TEMSCON EUROPE), Izmir, Turkey, 2022, pp. 1-6, doi: 10.1109/TEMSCONEUROPE54743.2022.9802008.
- Mohammad Abu Sufian, Zenith Matin Guria, Niaz Morshed, S M Tamim Hossain Rimon, Ahmed Inan Mosaddeque, Asif Ahamed, "Leveraging Machine Learning for Strategic Business Gains in the Healthcare Sector," 2024 International Conference on TVET Excellence & Development (ICTeD-2024), Melaka, Malaysia, 2024.
- W. Alomoush, T. A. Khan, M. Nadeem, J. I. Janjua, A. Saeed and A. Athar, "Residential Power Load Prediction in Smart Cities using Machine Learning Approaches," 2022 International Conference on Business Analytics for Technology and Security (ICBATS), Dubai, United Arab Emirates, 2022, pp. 1-8, doi: 10.1109/ICBATS54253.2022.9759024.
- J. I, M. Nadeem and Z. A. Khan, "Machine Learning Based Prognostics Techniques for Power Equipment: Comparative Study," 2021 IEEE International Conference on Computing (ICOCO), Kuala Lumpur, Malaysia, 2021, pp. 265-270, doi: 10.1109/ICOCO53166.2021.9673564.
- SM TH Rimon , Mohammad A Sufian, Zenith M Guria, Niaz Morshed, Ahmed I Mosaddeque, Asif Ahamed, "Impact of AI-Powered Business Intelligence on Smart City Policy-Making and Data-Driven Governance," International Conference on Green Energy, Computing and Intelligent Technology (GEn-CITy 2024), Johor, Malaysia, 2024.
- Asif Ahamed , Nisher Ahmed , Jamshaid Iqbal Janjua , Zakir Hossain, Ekramul Hasan, Tahir Abbas, "Advances and Evaluation of Intelligent Techniques in Short-Term Load Forecasting," 2024 International Conference on Computer and Applications (ICCA-2024), Cairo, Egypt, 2024.
- S. E. Bibri, "The IoT for smart sustainable cities of the future," Sustainable Cities and Society, vol. 38, pp. 230-253, 2018. doi: 10.1016/J.SCS.2017.12.034.
- M. Alzboon et al., "The characteristics of the green internet of things and big data in building safer, smarter, and sustainable cities," Applied Computing eJournal, 2019. doi: 10.12785/IJCDS/060403.
- J. Wu, "Construction of Smart City Application Areas," 2022 IEEE 2nd Int. Conf. on Mobile Networks and Wireless Communications (ICMNWC), pp. 1-5, 2022. doi: 10.1109/ICMNWC56175.2022.10031927.

- A. Alsaig et al., "Characterization and Efficient Management of Big Data in IoT-Driven Smart City Development," *Sensors (Basel)*, vol. 19, p. 2430, 2019. doi: 10.3390/s19112430.
- W. Wang and L. Li, "Optimization Method for Sustainable Development of Smart City Public Management Based on Big Data Analysis," *Int. J. Data Warehous. Min.*, vol. 19, pp. 1-17, 2023. doi: 10.4018/ijdw.322757.
- D. Dhabliya et al., "Utilizing Big Data and environmentally-focused innovations to create smart, sustainable cities," *2023 Int. Conf. on Tech. Eng. and Applications in Sustainable Dev.*, pp. 402-408, 2023. doi: 10.1109/ICTEASD57136.2023.10585061.
- Y. Zhang et al., "Big data and artificial intelligence-based early risk warning system of fire hazard for smart cities," *Sustainable Energy Technol. Assess.*, vol. 45, p. 100986, 2021. doi: 10.1016/J.SETA.2020.100986.
- A. Lavallo et al., "Improving Sustainability of Smart Cities through Visualization Techniques for Big Data," *Sustainability*, vol. 12, p. 5595, 2020. doi: 10.3390/su12145595.
- A. Sinaeepourfard, S. Shaik, and N. Mesgaribarzi, "Decentralized, Distributed, and Hybrid ICT Architectures," *2024 IEEE Conf. on Technologies for Sustainability (SusTech)*, pp. 345-355, 2024. doi: 10.1109/SusTech60925.2024.10553566.
- S. T. Ng, F. J. Xu, Y. Yang, and M. Lu, "A master data management solution to unlock the value of big infrastructure data for smart, sustainable and resilient city planning," *Procedia Eng.*, vol. 196, pp. 939-947, 2017. doi: 10.1016/J.PROENG.2017.08.034.
- Sun Ying, "Research on big data and new smart city construction," *2021 Int. Conf. on Education, Information Management and Service Science (EIMSS)*, pp. 31-36, 2021. doi: 10.1109/EIMSS53851.2021.00015.
- Z.-h. Xu, "Research on Urban and Rural Planning and Smart City Construction in Big Data Era," *IOP Conf. Ser.: Earth Environ. Sci.*, vol. 580, 2020. doi: 10.1088/1755-1315/580/1/012003.
- D. Dhabliya et al., "Utilizing Big Data and environmentally-focused innovations to create smart, sustainable cities," *2023 Int. Conf. on Tech. Eng. and Applications in Sustainable Dev.*, pp. 402-408, 2023. doi: 10.1109/ICTEASD57136.2023.10585061.
- A. Alsaig et al., "Characterization and Efficient Management of Big Data in IoT-Driven Smart City Development," *Sensors (Basel)*, vol. 19, p. 2430, 2019. doi: 10.3390/s19112430.
- Babu Nuthalapati, S., Nuthalapati, A., "Accurate Weather Forecasting with Dominant Gradient Boosting Using Machine Learning," *Int. J. Sci. Res. Arch.*, vol. 12, no. 2, pp. 408-422, 2024, doi:10.30574/ijrsra.2024.12.2.1246.
- M. A. Al-Tarawneh, R. A. AlOmoush, T. ul Islam, J. I. Janjua, T. Abbas and A. Ihsan, "Current Trends in Artificial Intelligence for Educational Advancements," *2024 International Conference on Decision Aid Sciences and Applications (DASA)*, Manama, Bahrain, 2024, pp. 1-6, doi: 10.1109/DASA63652.2024.10836340.
- Nadeem, N., Hayat, M.F., Qureshi, M.A. et al. "Hybrid Blockchain-based Academic Credential Verification System (B-ACVS)," *Multimed Tools Appl* 82, 43991-44019 (2023). doi: 10.1007/s11042-023-14944-7.
- T. Abbas, J. I. Janjua and M. Irfan, "Proposed Agricultural Internet of Things (AIoT) Based Intelligent System of Disease Forecaster for Agri-Domain," *2023 International Conference on Computer and Applications (ICCA)*, Cairo, Egypt, 2023, pp. 1-6, doi: 10.1109/ICCA59364.2023.10401794.

- Abdullah Al Noman, Md Tanvir Rahman Tarafder, S M Tamim Hossain Rimon, Asif Ahamed, Shahriar Ahmed, Abdullah Al Sakib, "Discoverable Hidden Patterns in Water Quality through AI, LLMs, and Transparent Remote Sensing," The 17th International Conference on Security of Information and Networks (SIN-2024), Sydney, Australia, 2024, pp. 259-264.
- A. Rehman, F. Noor, J. I. Janjua, A. Ihsan, A. Q. Saeed and T. Abbas, "Classification of Lung Diseases Using Machine Learning Technique," 2024 International Conference on Decision Aid Sciences and Applications (DASA), Manama, Bahrain, 2024, pp. 1-7, doi: 10.1109/DASA63652.2024.10836302.
- Md Tanvir Rahman Tarafder, Md Masudur Rahman, Nisher Ahmed, Tahmeed-Ur Rahman, Zakir Hossain, Asif Ahamed, "Integrating Transformative AI for Next-Level Predictive Analytics in Healthcare," 2024 IEEE Conference on Engineering Informatics (ICEI-2024), Melbourne, Australia, 2024.
- J. I. Janjua, M. Irfan, T. Abbas, A. Ihsan and B. Ali, "Enhancing Contextual Understanding in Chatbots and NLP," 2024 International Conference on TVET Excellence & Development (ICTeD), Melaka, Malaysia, 2024, pp. 244-249, doi: 10.1109/ICTeD62334.2024.10844601.
- Asif Ahamed , Md Tanvir Rahman Tarafder , S M Tamim Hossain Rimon , Ekramul Hasan , Md Al Amin, "Optimizing Load Forecasting in Smart Grids with AI-Driven Solutions," 2024 IEEE International Conference on Data & Software Engineering (ICoDSE-2024), Gorontalo, Indonesia, 2024.
- J. I, A. Sabir, T. Abbas, S. Q. Abbas and M. Saleem, "Predictive Analytics and Machine Learning for Electricity Consumption Resilience in Wholesale Power Markets," 2024 2nd International Conference on Cyber Resilience (ICCR), Dubai, United Arab Emirates, 2024, pp. 1-7, doi: 10.1109/ICCR61006.2024.10533004.