International Journal of Scientific Research and Engineering Development-– Volume 7 Issue 1, Jan-Feb 2024

Available at www.ijsred.com

RESEARCH ARTICLE OPEN ACCESS

# Integration Of Machine Learning Techniques in Banana Production: A Literature Review

Rhen John Rey R. Sacala[1],Jesie B. Abad[2], Edwin R. Arboleda[3]

[1]*Department of Computer, Electronics and Electrical Engineering, Cavite State University – Main Campus, Indang, Cavite, Philippines*
Email:rhenjohnrey.sacala@cvsu.edu.ph

[2]*Department of Computer, Electronics and Electrical Engineering, Cavite State University – Main Campus, Indang, Cavite, Philippines*
Email: jesie.abad@cvsu.edu

[3]*Department of Computer, Electronics and Electrical Engineering, Cavite State University – Main Campus, Indang, Cavite, Philippines*
Email:edwin.r.arboleda@cvsu.edu.ph

----------------------------------------************************----------------------------------

## Abstract:

As a crop cultivated throughout the country, bananas have been an integral crop mainly produced for its economic value. Such production needs an improvement in streamlining the process in order to ensure the profitability of the crop and meeting the demand of the fruit across the world. As an emerging technology, machine learning have been employed in agriculture by assessing different factors brought about by a crop. The significance of classifying bananas in determining crop quality and market value is emphasized in this article. By expanding on earlier research to uncover critical techniques for enhancing banana quality assessment, it highlights the revolutionary influence of machine learning algorithms on this process. Notable gains in speed and precision have resulted from the innovations outlined, setting the stage for significant future expansion. Utilizing machine learning techniques to their fullest potential can aid future studies tackling issues pertaining to food security and sustainable agriculture.

*Keywords* **—Banana Production, Machine Learning, Algorithm, Image Classifier, Quality Assessment, Neural Networks, Remote Sensing**

----------------------------------------************************----------------------------------

## I. INTRODUCTION

### A. *Importance of Bananas and Challenges in Production*

Bananas are important fruit crops with high nutritional value and are widely consumed worldwide [1] [2] [3]. They are a rich source of carbohydrates, vitamins (particularly vitamin B), potassium, phosphorus, calcium, and magnesium [4]. Bananas are easy to digest, free from fat and cholesterol, and provide various health benefits such as reducing the risk of cardiovascular diseases and cancer, acting as antioxidants, and having antimicrobial and anti-inflammatory properties. They are also economically significant, contributing to food security and income generation through local and international trade.

The challenges in the production of bananas include increasing production costs, pests and diseases, yield uncertainties, labor scarcity, high labor cost, non-availability of good quality suckers, inadequate power supply, high cost of inputs, inadequate water supply during summer, insufficient credit facilities, fixation of price by commission agents, lack of cold storage facilities, improper weighing procedures, perishability of the banana, price fluctuation, inadequate transport facilities, resistant breakdown, monoculture, illegal use of chemicals, multiple infections, low genetic base in banana, gene flow, and climate change [5] [6] [7] [8]. These challenges not only affect the livelihoods of smallholder farmers but also contribute to the erosion of certain banana varieties and the loss of the region's dominance in banana production [9]. To address these challenges, it is crucial to provide smallholder farmers with correct information, access to technology, and increased support. Additionally, intensive cultivation with improved cultivars and the use of agricultural inputs can help overcome these constraints. Biotechnological approaches, such as application of machine learning techniques, also hold promise for improving banana production.

### *B. Emergence of Machine Learning (ML) and its Potential in Agriculture*

Machine learning is an emerging technology in agriculture that has the potential to revolutionize the industry. It can be used for various applications such as crop yield prediction, disease detection, soil analysis, irrigation control, and automation of farm equipment [10] [11]. Traditional methods of yield estimation and disease detection are often slow and inaccurate, but machine learning algorithms can accurately predict crop yields and provide efficient detection methods for diseases and pests [12] [13]. By integrating machine learning with Internet of Things (IoT) devices, data collected from agricultural fields can be analyzed to optimize crop yield, reduce resource consumption, and improve farm management [14]. Machine learning techniques can also benefit farmers by suggesting the best crop for a particular plot of land based on soil parameters and meteorological circumstances, leading to increased profit margins and avoidance of soil pollution. Overall, machine learning has the potential to improve agricultural practices, increase food security, and enhance the quality and quantity of agricultural products.

### *C. Scope and Objectives*

This literature review aims to comprehensively synthesize the latest research, gathered from numerous available databases online on the utilization of machine learning techniques in the production of bananas. The main goal of this paper is to provide a comprehensive analysis of the current state of banana production including its benefits and challenges faced by its farmers. The review will assess the effectiveness of utilizing machine learning techniques in improving the production process of bananas by detecting pests and diseases, monitoring and grading the fruit, assessing soil quality parameters and predicting and optimizing expected yield of the crop. Moreover, the paper will also cite the challenges of utilizing such techniques and its future direction upon implementation in banana farms.

## II. APPLICATIONS OF ML IN BANANA PRODUCTION

### *A. Disease and Pest Detection*

1) ***Image-based approaches for identifying specific diseases and pests:*** Image-based approaches have been used to identify specific pests and diseases in bananas. One study proposed a deep learning model called BananaSqueezeNet, which achieved an overall accuracy of 96.25% in diagnosing banana leaf diseases from images [15]. Another study utilized machine learning and deep learning techniques, such as image processing and Convolutional Neural Networks, to detect various diseases in banana plants, enabling early detection and minimizing yield loss [16]. Additionally, a deep learning-based algorithm was developed for the classification of three important leaf spot diseases in bananas, achieving an accuracy of 91.7% [17]. Furthermore, a method combining image preprocessing, segmentation, and gray level co-occurrence matrix (GLCM) extraction, followed by classification using Convolutional Deep Neural Networks (CDNN), was proposed for detecting diseases in banana fruit [18]. These image-based approaches provide effective tools for identifying and managing pests and diseases in banana crops.

2) ***Sensor data analysis for early detection and preventative measures:*** Sensor data analysis plays a crucial role in the early detection and prevention of diseases in bananas. By analyzing the data collected from sensors, farmers and extension officers can identify the presence of diseases at an early stage, allowing them to take prompt and appropriate measures to prevent the spread of diseases and minimize crop loss. The analysis of sensor data enables the development of effective disease detection models, such as deep learning models trained for the detection of banana diseases [19]. These models can be deployed on smartphones, providing a convenient and accessible

  

tool for farmers to detect diseases in real-time [20]. Additionally, sensor data analysis allows for the identification of distinguishable features that indicate the presence of diseases, improving the accuracy of disease detection [21]. Overall, sensor data analysis empowers farmers and extension officers with the necessary tools and information to detect and prevent diseases in bananas, ultimately improving agricultural productivity and yield [22].

### B. Yield Prediction and Optimization

1) ***ML models for forecasting banana yield based on environmental factors and management practices:*** Through machine learning models, relying on data gathered on environmental factors and management practices the yield of banana crop is predicted. Such models utilize historical data such as rainfall, temperature, fertilizer, and past crop yield data to make accurate predictions. Various machine learning algorithms, including ensemble XGBoost-RF, gradient boosting, random forest, and XGBoost, have been employed for this purpose. The ensemble XGBoost-RF model has shown maximum accuracy in predicting banana yield, with an R2 of 0.976111 and MSE of 0.002163 [23]. Additionally, remote sensing-based approaches using satellite image time series have been explored to forecast banana yield at the field scale. These approaches involve the use of vegetation indices derived from satellite data, such as Normalised Difference Vegetation Index (NDVI), Leaf Area Index (LAI), Enhanced Vegetation Index (EVI), and Normalised Difference Water Index (NDWI), along with other climatic variables like evapotranspiration (ET) [24] [25].

2) ***Optimizing resource allocation, irrigation, and fertilization using ML algorithms:*** Aside from forecasting the expected yield of a banana, machine learning algorithms help in optimizing the allocation of vital resources for the crop such as irrigation and application of fertilizers. These algorithms use intelligent sensor approaches to plan operations and missions with limited resources and little human involvement in agriculture [26]. They optimize water use, supply the field with needed water and fertility, increase output, decrease handling, and decrease crop disease [27]. Machine learning models can provide intelligent irrigation management by integrating with mobile and web platforms [28]. They can also predict crop yield and recommend fertilizer based on soil characteristics and weather conditions [29]. Machine learning techniques learn from environmental data sets to estimate crop yield and provide corrective measures for yield optimization [30]. They can also detect plant diseases and suggest enhancements for soil fertility. Additionally, machine learning technology can be used in precision irrigation schemes to simulate human decision-making and resolve problems affecting irrigation management.

### C. Fruit Quality Monitoring and Grading

1) ***Automated systems for non-destructive ripeness assessment and defect detection:*** Automation is used in assessing the ripeness of bananas through the application of computer vision and machine learning techniques. These methods aim to overcome the limitations of manual classification, which is subjective and time-consuming. Various models have been proposed to automate the ripeness assessment of bananas. One approach involves using the HSV color model and a Multiclass Support Vector Machine (SVM) based on OVO with an RBF kernel function [31]. Another approach utilizes a Convolutional Neural Network (CNN) to classify different ripeness stages of bananas, achieving high accuracy [32]. Additionally, a hybrid model combining deep learning models like VGG-16 and ResNet-50 for feature extraction, along with a machine learning classifier, has been proposed [33]. Furthermore, multi-spectral imaging combined with Support Vector Machine (SVM) prediction scores has been explored to detect artificially ripened bananas [34]. These automated methods offer more accurate and efficient ways to assess the ripeness of bananas.

2) ***Development of AI-powered sorting and grading systems for efficient post-harvest management:*** Artificial Intelligence (AI) is used in sorting and grading banana fruits through the application of deep learning models such as ResNet50, EfficientNetB7, and NasNetLarge. These models are trained on banana datasets to classify the fruits into different categories based on their quality and ripeness [35] [36] [37] [38]. The use of AI in this process offers several advantages, including the ability to automate the sorting and grading process, improve accuracy, reduce labor and time requirements, and enhance overall production rates [39]. AI models can analyze images of bananas and accurately determine their maturity stages, size, and perspective, achieving high levels of accuracy and robustness. By integrating RGB imaging and hyperspectral imaging, AI models can further improve the classification of bananas and potentially be applied to other horticultural products. The implementation of AI in sorting and grading bananas is expected to pave the way for automated systems in on-farm fruit sorting and transportation.

### D. Other Applications

1) ***Soil health analysis and agriculture techniques:*** The application of precision agriculture methods has the potential to enhance soil health in banana cultivation [40]. Precision agriculture relies on advanced technologies such as global navigation satellite systems (GNSS), geographic information systems

(GIS), and remote sensing to gather and analyze spatial variability data within the field. This empowers farmers to make informed decisions regarding the management of soils and crops, encompassing precision seeding, variable rate fertilizer application, and targeted pesticide usage [41]. Furthermore, precision agriculture can contribute to the effective management of soil fertility by offering recommendations based on soil nutrient analysis, thereby leading to improved crop yield [42]. In the realm of agriculture, machine learning techniques can also be employed to analyze soil health, with decision tree models displaying promising outcomes [43]. By integrating precision agriculture techniques and utilizing machine learning models, farmers can optimize resource utilization, decrease inputs, and enhance productivity in banana production.

2) ***Robotics and automation in banana plantations:*** Robotics and automation have the capacity to address labor shortages and reduce costs in the de-handing operation in banana plantations [44]. However, the intricate environment of banana orchards and the aging farming population present challenges to the implementation of mechanized de-handing systems [45]. Scholars have proposed sophisticated techniques to facilitate the development of mechanical de-handing systems, but the successful adoption of this technology still encounters obstacles [46]. Within the field of agriculture, automation and agribots have been investigated for various tasks, including the design of control algorithms for navigation and identification of landmarks in row-type plantations [47]. Moreover, robotic pruning systems are enhancing plant health by maneuvering through plantations to trim excess leaves and eliminate diseased or damaged parts [48]. Drones equipped with sensors and cameras are assisting in pest and disease management by monitoring plantations for early signs of infestations or nutrient deficiencies, thus permitting targeted interventions [49]. Automated irrigation and fertilization systems are offering precise delivery of water and nutrients based on the specific requirements of plants, thereby conserving resources and maximizing growth potential [7]. Advanced data analytics and machine learning algorithms are analyzing sensor data to provide insights into crop health, growth patterns, and environmental conditions, thereby enabling data-driven decision-making for optimized production [50]. These technologies, combined with predictive analytics for harvest timing and logistics, are transforming banana cultivation, rendering it more sustainable, efficient, and resilient to challenges such as labor shortages and climate variability [51][52].

  

*E. Literature Review Findings*

TABLE I
FINDINGS ON THE IMPLEMENTATION OF MACHINE LEARNING IN DISEASE AND PEST DETECTION IN BANANAS

| Lead Author and Year | Title | Database Searched | Number of Studies Included | Findings |
|---|---|---|---|---|
| Bhuiyan, M. (2023) | BananaSqueezeNet: A very fast, lightweight convolutional neural network for the diagnosis of three prominent banana leaf diseases | Elsevier, Smart Agricultural Technology | 49 | Creating a new deep learning model specialized for detecting banana leaf diseases, the proposed model achieved an impressive accuracy of 96.25%, a precision of 96.53%, recall of 96.25%, and specificity 98.75% in disease diagnosis. It outperformed other popular models like EfficientNetB0 and ResNet-50. |
| Jadhav, S. (2023) | Banana Crop Disease Detection Using Deep Learning Approach | International Journal for Research in Applied Science & Engineering Technology | 5 | By employing image processing and passing the images through a Convolutional Neural Network, the detection of banana leaf diseases was done and it achieved an accuracy of 88.32% |
| Mahendran, T. (2023) | Feature Extraction and Classification Based on Pixel in Banana Fruit for Disease Detection Using Neural Networks | IEEE, 2023 Third International Conference on Advances in Electrical, Computing, Communication and Sustainable Technologies (ICAECT) | 15 | The authors propose a method combining image pre-processing, segmentation, feature extraction, and classification to detect banana fruit diseases. The proposed method effectively detects the diseases by simulation; however, it still needs validation through usage of real data |
| Mathew, D. (2023) | Classification of leaf spot diseases in banana using pre-trained convolutional neural networks | IEEE, 2023 International Conference on Control, Communication and Computing (ICCC) | 21 | Using a deep learning approach and convolutional neural networks and augmentation of pre-training data. Comparing with other |

| | | | | |
|---|---|---|---|---|
| | | | | built models, DenseNet 121 model achieved the highest accuracy of 91.7% promising a potential for automation of disease detection. |
| Nandhini, A. (2023) | A smart agriculturing IoT system for banana plants disease detection through inbuilt compressed sensing devices | Springer Link, Multimedia Tools and Applications | 35 | By creating a prototype using Raspberry Pi with camera and sensors for environmental data, image analysis was done to clearly pinpoint and identify diseases present in the leaves of banana. The proposed prototype resulted in an accuracy of 97.65% for disease detection and 97.33% for subsequent classification of the detected disease. |
| Subramani, S. (2022) | Classification Learning Assisted Biosensor Data Analysis for Preemptive Plant Disease Detection | ACM, ACM Transactions on Sensor Networks | 24 | Using biosensors, the authors proposed using PC-DD technique for early and accurate disease detection, enabling analysis of incomplete sensor data. However, as this was evaluated theoretically, further evaluation using real-world biosensor data is required. |

TABLE II
YIELD PREDICTION AND RESOURCE OPTIMIZATION USING MACHINE LEARNING APPROACHES

| Lead Author and Year | Title | Database Searched | Number of Studies Included | Findings |
|---|---|---|---|---|
| Silva, A. (2023) | Yield prediction in banana (Musa sp.) using STELLA model | Acta Scientiarum, Agronomy | 29 | A model was developed using STELLA software to estimate the growth and productivity of bananas under irrigation. The proposed model accurately predicts the productivity of the plant under specific conditions. However, it still needs further validation and testing in varying conditions outside of the locale of the study. |
| Pandya, U. (2023) | Forecasting of Banana Crop Productivity Using Geospatial Approach: A Case Study of Anand District | MDPI, Environmental Sciences Proceedings | 7 | Using available data from Sentinel and Landsat satellites, data such as vegetation indices, land surface temperature, and evapotranspiration were analysed. It was found out that there is a strong correlation in between banana yield and the availability of water. This further demonstrated the potential of using satellite data in predicting future banana yields. |
| Devan, K. (2023) | Crop Yield Prediction and Fertilizer Recommendation System Using Hybrid Machine Learning Algorithms | IEEE, 2023 IEEE 12th International Conference on Communication Systems and Network Technologies (CSNT) | 10 | By developing a hybrid machine learning system, prediction of crop yields was made possible. The proposed system combined Random Forest and Logistic Regression. Evaluating the system enabled the farmers to make informed decision regarding suitable crops for |

  

| | | | | |
|---|---|---|---|---|
| | | | | planting and the recommended fertilizer to be applied. |
| Premasudha, B. (2022) | ML based methods XGBoost and Random Forest for Crop and Fertilizer Prediction | IEEE, 2022 14th International Conference on Computational Intelligence and Communication Networks (CICN) | 21 | By utilizing machine learning techniques, the author proposed that systems should be developed that has the ability to predict crop suitable for planting, recommend fertilizers based on nutrients inherent on soil, and detect plant diseases from leaf images. This can be achieved by using Random Forest algorithm and image recognition. |
| Aruna, M. (2023) | Arithmetic Optimization Algorithm with Machine Learning based Smart Irrigation System in IoT Enviro | IEEE, 2023 Fifth International Conference on Electrical, Computer and Communication Technologies (ICECCT) | 18 | By developing a smart irrigation system and utilizing a data-driven approach, precision irrigation is achieved. Such approach utilizes IoT and ML technologies. Further decisions are optimized using multilayer perceptron model and arithmetic optimization algorithm (AOA). Using the proposed system, it outperformed other models in irrigation classification accuracy. |

  

TABLE III
FRUIT QUALITY MONITORING AND GRADING USING MACHINE LEARNING

| Lead Author and Year | Title | Database Searched | Number of Studies Included | Findings |
|---|---|---|---|---|
| Enríquez, J. (2023) | Artificial Intelligence-Based Banana Ripeness Detection | SpringerLink | 30 | The research paper proposes an artificial intelligence model for detecting the ripeness level of bananas based on the Von Loesecke scale. Leveraging the HSV color model, the model employs a Multiclass Support Vector Machine (SVM) with an RBF kernel function. The accuracy achieved by this approach is 98.89%, surpassing existing methods |
| Saranya, N. (2023) | FBCNN-TSA: An optimal deep learning model for banana ripening stages classification | IOS PRESS | 33 | The proposed model outperforms cutting-edge computer vision-based algorithms in both coarse and perfectly acceptable classification of maturation phases. The experimental results using images of bananas at various stages of ripening, achieves overall accuracy of 96.9%. |
| Baglat, P. (2023) | Non-Destructive Banana Ripeness Detection Using Shallow and Deep Learning: A Systematic Review | MPDI | 47 | The research paper proposes an artificial intelligence model for detecting the ripeness level of bananas based on the Von Loesecke scale. Leveraging the HSV color model, the model employs a Multiclass Support Vector Machine (SVM) with an RBF kernel function. The accuracy achieved by this approach is 98.89%, surpassing existing methods |

  

| | | | | |
|---|---|---|---|---|
| Mathew, M. (2023) | Banana Ripeness Identification and Classification Using Hybrid Models with RESNET-50, VGG-16 and Machine Learning Techniques | Machine Intelligence Techniques for Data Analysis and Signal Processing | 25 | The research paper proposes an artificial intelligence model for detecting the ripeness level of bananas based on the Von Loesecke scale. Leveraging the HSV color model, the model employs a Multiclass Support Vector Machine (SVM) with an RBF kernel function. The accuracy achieved by this approach is 98.89%, surpassing existing methods |

TABLE IV
OTHER APPLICATIONS UTILIZING MACHINE LEARNING APPROACHES

| Lead Author and Year | Title | Database Searched | Number of Studies Included | Findings |
|---|---|---|---|---|
| Shaheb, R. (2021) | Precision Agriculture for Sustainable Soil and Crop Management | Soil Science - Emerging Technologies, Global Perspectives and Applications | 127 | Precision agriculture utilizes technologies such as GNSS, GIS, remote sensing, and variable rate application to analyze spatial variability in agricultural fields, allowing for site-specific management decisions that optimize resource use, enhance profitability, and promote sustainable soil and crop management practices. |
| Deone. J., (2023) | Techniques applied to increase soil fertility in smart agriculture | Academic Press | 23 | The study proposes an ensemble model-based recommendation system for precision farming to address inadequate and imbalanced fertilization, while also highlighting the potential of nuclear technology to improve soil fertility and crop yield in India, aiming to increase |

| | | | | |
|---|---|---|---|---|
| | | | | productivity while minimizing ecological impacts. |
| Ahmad, M. (2023) | Addressing Agricultural Robotic (Agribots) Functionalities and Automation in Agriculture Practices: What's Next? | Advances in Agricultural and Food Research Journal | 26 | The developed algorithms showed their robustness by precisely distinguishing and mapping the crop rows with a 100% accuracy, while the inter-row weed patches with an accuracy of 85%, and it was proposed to detect the early growth stage based on the weed maps through site-specific weed management. |
| Guo, J. (2022) | De-Handing Technologies for Banana Postharvest Operations Updates and Challenges | MPDI | 82 | The paper systematically reviews existing research on de-handing technologies for bananas, evaluating mechanism design feasibility, model simulation stability, and prototype system reliability, while also discussing future challenges and opportunities for practical adoption. |
| Bahadure, R. (2018) | Design and development of automated banana pruning machine | International Journal of Mechanical and Production Engineering Research and Development | 29 | The study efficiently produces round-shaped leaf spreads from banana leaves, addressing cost-saving concerns for hotels. It increases the production rate to 100 plates per hour, overcoming manual labor limitations and ensuring economic benefits while minimizing leaf consumption |
| Gopinath, S. (2020) | Application of drones in agriculture: A comprehensive review | Journal of Agriculture and Environmental Sciences | 72 | The usage of drones in agriculture has significantly improved crop health monitoring, weed |

  

| | | | | |
|---|---|---|---|---|
| | | | | management, and other farm operations, leading to enhanced productivity and better agricultural outputs |
| Lu, X. (2019) | An intelligent agricultural irrigation system based on Internet of Things. | IEEE | 25 | The artificial neural network (ANN) algorithm proves to be the most accurate choice for an intelligent irrigation system, effectively minimizing water loss for various products |
| Ceballos, G. (2018) | Application of machine learning in agriculture: A systematic review | Computers and Electronics in Agriculture | 28 | The systematic review of machine learning applications in agricultural supply chains (ASCs) reveals that ML techniques can enhance ASC sustainability by providing real-time analytic insights for data-driven decision-making, ultimately improving agricultural productivity and sustainability |
| Kansal, A. (2021) | Impact of Climate Change on Agriculture: A Review of the Major Challenges and Adaptation Strategies in Banana Cultivation | Journal of Agrometeorolo | 72 | The impact of climate change on agriculture is multifaceted, affecting crop productivity, pest infestation, and soil microbial activities. Increased temperatures, CO2 concentration, and altered growth patterns pose challenges for global food security and economic stability |

  

# III. CHALLENGES AND FUTURE DIRECTIONS

## A. Challenges in Machine Learning Techniques for Banana Production

1) ***Data Collection and Annotation:*** Acquiring high-quality annotated data for training machine learning models in the field of banana production poses a considerable challenge due to the inherent variability in environmental conditions, plant health, and fruit characteristics. The process of gathering and annotating data for the purpose of training machine learning models plays a crucial role in determining their performance [53]. The emergence of data-centric artificial intelligence, which assigns primary importance to data, has brought about a paradigm shift in software development, underscoring the significance of high-quality data [54]. In the realm of deep learning applications, data collection assumes a pivotal role, and employing techniques such as data validation, cleaning, and integration can greatly enhance the quality of the data [55]. Furthermore, the quality of annotated data exerts a substantial influence on the accuracy of machine learning models that aim to predict subjective impressions [56. In fields where manual annotation poses challenges, the utilization of active learning-based approaches that leverage human annotation efforts can prove to be highly effective in generating training datasets of superior quality [57].

2) ***Model Generation:*** Ensuring the generalization of machine learning models across different varieties of bananas, diverse growing conditions, and various geographical locations is of utmost significance for widespread adoption and efficacy. However, the matter of developing models that yield consistent outcomes when tested within different contexts has received limited attention. Abdaljalil et al. delve into the investigation of model and data generalization in Arabic sentiment analysis, discovering that employing a cascaded approach involving two models - one for labeling neutral tweets and another for identifying positive/negative tweets based on the Arabic emoji lexicon - achieves the most consistent results [58]. Shultzman et al. demonstrate that model-based neural networks demonstrate superior generalization capability in comparison to ReLU neural networks for sparse recovery tasks, and they provide guidelines for constructing model-based networks that guarantee high generalization. Akrout et al. discuss the significance of domain generalization in wireless applications, wherein models must be able to generalize to unseen new domains without requiring additional finetuning [59].

3) ***Real-time Monitoring and Decision Making:*** Implementing real-time monitoring systems for the cultivation of bananas necessitates efficient data processing, model inference, and integration with preexisting farm management practices. In order to predict quality and classify the maturity level of bananas, a digital 12-channel flexible Vis/NIR optical sensing system was devised and implemented [60]. This particular system successfully identified various quality parameters of bananas and proposed a novel method for classifying their maturity level with a high degree of accuracy [61]. Furthermore, the utilization of Internet of Things (IoT) technology in real-time monitoring systems holds promise for enhancing livestock and crop management practices, augmenting productivity, and elevating the overall efficiency of the agricultural sector [62]. Smart farming systems based on IoT have the capability to furnish real-time data on moisture levels and temperature, as well as ecological surveillance of soil moisture efficiency, thereby enabling farmers to optimize both yield and harvest quality [63]. The continuous monitoring of soil moisture and plant health through the use of electroconductive sensors can aid farmers in making well-informed decisions pertaining to watering schedules and nutrient management, thereby facilitating optimal crop growth [64]. Lastly, real-time locating systems present potential advantages for the manufacturing industry, such as data acquisition, the reconfiguration of production systems, and the dynamic coordination of production orders.

4) ***Interpretability and Trust:*** Enhancing the comprehensibility of machine learning models is of utmost importance when it comes to instilling confidence among farmers and stakeholders in making critical decisions regarding crop management and resource allocation. The trustworthiness of machine learning hinges on its ability to be easily understood, yet many models remain opaque. One potential solution is to train models that are interpretable or to use them to imitate black-box models. Nevertheless, interpretable models can still be challenging to comprehend due to their size and complexity [65]. To tackle this issue, a fresh framework has been proposed that integrates interpretable components and visualization techniques to enhance the transparency and dependability of deep learning models. This approach combines saliency maps, feature attribution, and local interpretable model-agnostic explanations (LIME) to offer

  

comprehensive insights into the decision-making process of the model. By improving interpretability without compromising performance, this framework facilitates a better comprehension and trust in AI systems [66].

### B. Future Directions in Machine Learning Techniques for Banana Production

1) ***Integration of Multi-Modal Data:*** Integration of multi-modal data derived from satellite imagery, drone-based remote sensing, and IoT sensor networks possesses the ability to furnish comprehensive insights into banana plantations, thereby facilitating more robust and accurate predictions [67]. By fusing different data modalities, the efficacy of machine learning algorithms can be enhanced, thus augmenting prediction performance. Various methodologies have been proposed to tackle the challenges associated with collecting paired data from multiple modalities, including end-to-end training of neural networks on all available modalities and a two-phase multi-stream fusion approach [68]. Furthermore, the utilization of modality-shared and -specific features can assist in the annotation and integration of single-cell and spatial omics data [69]. Additionally, a pioneering method for multi-temporal urban mapping has been devised, leveraging multi-modal satellite data to effectively exploit the diverse data modalities and address the issue of missing optical modality attributed to cloud cover [70].

2) ***Deployment of Transfer Learning Frameworks:*** Transfer learning frameworks that utilize pre-existing models and domain-specific expertise can accelerate the process of training and adapting models for banana production tasks, thereby reducing the need for extensive annotated datasets. These frameworks employ a pre-trained model, developed based on a source domain, as a foundation and subsequently modify it to suit a target domain with a similar data distribution [71]. They showcase their ability to generalize to the target process by determining the generalization error of the models. Furthermore, a framework based on scoring is introduced to assess the transferability of pre-trained speech models for the purpose of fine-tuning target tasks [72][73]. This framework efficiently calculates transferability scores without actually fine-tuning candidate models or layers. These approaches to transfer learning have exhibited promising outcomes in diverse domains, encompassing natural language processing and computer vision.

3) ***Deployment of Edge Computing Solutions:*** Edge computing has emerged as a solution to address the challenges of connectivity, latency, and data privacy in various applications. In the context of banana plantations, deploying edge computing solutions can enable autonomous and real-time decision support systems for on-device model inference and decision-making. This involves placing services on edge nodes, carefully allocating computation resources, and considering the stochastic arrivals of tasks and the waiting time of unprocessed tasks. Deep reinforcement learning techniques can be used to make joint service placement and computation resource allocation decisions, with the objective of minimizing the total latency of tasks in the long term. Additionally, the deployment of parallelized service function chains (P-SFCs) and idle backup virtualized network functions (BVNFs) can enhance reliability and reduce delay in multi-access edge computing (MEC) networks [74]. Experimental results show that edge offloading can effectively reduce latency and offer significant advantages for real-time applications [75].

4) ***Emphasis on Explainable AI:***Explainable AI techniques have gained importance in recent years, aiming to enhance the transparency, interpretability, and trustworthiness of machine learning models. These techniques enable humans to understand and validate the predictions made by AI models effectively. The use of Explainable AI is particularly relevant in the context of banana production, as it empowers farmers to gain insights into the decision-making process of AI models and validate their predictions. By providing explanations for the model's output, farmers can understand the factors that contribute to the predictions and make informed decisions based on this information. Several techniques, such as saliency maps, attention mechanisms, and rule-based explanations, have been developed to enhance interpretability in AI models [76] [77] [78].

5) ***Collaborative Research and Adoption:*** Collaborative research efforts between academia, industry, and agricultural communities can play a crucial role in developing and validating machine learning solutions for banana production [79]. This collaboration can help tailor these solutions to the specific needs and challenges of the industry, leading to sustainable adoption and impact at scale [80]. By bringing together different stakeholders, such as researchers, farmers, and industry experts, collaborative research can ensure that the developed solutions are practical,

  

effective, and aligned with the goals of all involved parties [81]. Additionally, this collaborative approach can facilitate knowledge sharing, capacity building, and the transfer of technology and innovation between academia, industry, and agricultural communities [82] [83]. By fostering these collaborative research efforts, we can enhance the adoption of machine learning solutions in banana production, leading to improved productivity, sustainability, and overall outcomes for the industry.

## IV. CONCLUSIONS

### A. Summary of Key Findings and Potential Impact of ML on Banana Production

In agriculture, particularly in the production of bananas, machine learning (ML) approaches have been used to solve a number of problems, including disease diagnosis, crop yield prediction, and fertilizer application optimization. Based on epidemiological factors of illnesses like Black Sigatoka, machine learning (ML) models, including random forests (RF), have demonstrated great accuracy in predicting the quantity of banana bunches [84]. Early detection of banana illnesses has been achieved by image processing and soft computing approaches; case-based reasoning has been proven to be inferior to the Adaptive Neuro-Fuzzy Inference System [85]. Furthermore, fruit yield and other attributes have been successfully predicted by machine learning (ML) models such as the multilayer perceptron (MLP) and generalized regression neural network (GRNN), with GRNN surpassing MLP [86]. It has been discovered that applying organic fertilizers on a regular basis enhances the microbial activity and soil chemical quality, which supports sustainable banana production [87].

In order to aid in early diagnosis and efficient disease management techniques, researchers have demonstrated impressive accuracy in disease identification and categorization based on leaf symptoms [88][89]. Furthermore, machine learning (ML)-based models for yield prediction have been created, utilizing agronomic and environmental data to produce accurate projections and assist in crop management decision-making [90]. With climate change and new pests and illnesses, there is great potential for these developments in ML-driven technologies to optimize resource allocation, boost production, and guarantee sustainable banana growing techniques. Jayasundara et al. (2020) conducted a study that showcased the efficacy of machine learning algorithms in determining the ideal circumstances for banana ripening, improving post-harvest management techniques, and decreasing food waste [91]. Additionally, Tripathi et al. (2018)'s work demonstrated the effectiveness of machine learning (ML)-based models for forecasting banana production under various meteorological circumstances, offering insightful information for crop planning and risk mitigation techniques [92]. Furthermore, research conducted in 2019 by Mishra et al. demonstrated the application of ML in pest and disease forecasting, allowing for preventive steps to protect banana crops and enhance overall farm resilience [93].

Further research by Khan et al. (2021) investigated the integration of ML approaches in improving irrigation management practices for banana agriculture, leading to enhanced yield results and water usage efficiency [94]. This research was conducted in addition to the previously described studies. Similar to this, Kumar et al. (2017) looked at the use of ML algorithms to analyze nutrient levels and soil parameters, providing information for customized fertilization plans and precision agriculture in banana plantations [95]. Furthermore, Patel et al.'s (2020) research concentrated on using ML for real-time disease detection in banana plants, allowing for prompt interventions to reduce crop losses and slow the spread of illness [96]. By examining meteorological data, soil characteristics, and agricultural practices, Silva et al. (2020) created prediction models to estimate banana production in Brazil [97]. A further investigation conducted by Sharma and colleagues (2021) examined machine learning (ML) approaches for controlling pests and diseases in banana plantations, highlighting the significance of precision agriculture in augmenting crop yield and sustainability [98]. In addition, Yang et al. (2019) conducted further study on the use of deep learning approaches for the identification of banana diseases, providing insights into automated disease diagnosis and prompt actions to reduce yield losses [99]. These findings highlight the potential impact of ML in enhancing disease identification, yield prediction, and soil management in banana production.

### *B. Future Research Directions and Opportunities for Advancement*

Future areas of investigation and possibilities for advancement in the realm of banana cultivation using machine learning methodologies encompass the creation of profound learning models designed for the identification of banana leaf diseases [100]. These models, including BananaSqueezeNet, have demonstrated remarkable precision in detecting diseases such as Pestalotiopsis, Sigatoka, and Cordana, as well as other ailments that impact banana leaves, fruits, and stems. Another field of inquiry pertains to the utilization of image processing and profound learning to assess the maturity, categorization, and prognostication of banana fruits [101]. This could facilitate farmers, markets, and traders in the sorting and delivery of bananas that exhibit appropriate quality. In addition, the implementation of machine learning techniques, such as convolutional neural networks, could assist in the identification of diseases in banana fruits, thereby leading to enhanced agricultural efficiency [102]. These advancements in image processing and machine learning hold the potential to augment banana production and contribute to the agricultural sector.

## REFERENCES

[1] Swain, S., Pradhan, B., & Patil, P. (2020). Evaluating efficacy of high density planting in banana under coastal plain zone of Odisha. International Journal of Current Microbiology and Applied Sciences, 9(11), 152–160. https://doi.org/10.20546/ijcmas.2020.911.018

[2] Mostafa, H. S. (2021). Banana plant as a source of valuable antimicrobial compounds and its current applications in the food sector. Journal of Food Science, 86(9), 3778–3797. https://doi.org/10.1111/1750-3841.15854

[3] Luiz, L. C., Nascimento, C. A., Bell, M. J. V., Batista, R. T., Meruva, S., & Anjos, V. (2022). Use of mid infrared spectroscopy to analyze the ripening of Brazilian bananas. Food Science and Technology, 42. https://doi.org/10.1590/fst.74221

[4] Sumi, K., Banik, S., &Chakruno, P. (2022). Current status of banana (Musa Paradisiaca L.) diseases and their management. Diseases of Horticultural Crops, 109–140. https://doi.org/10.1201/9781003160397-6

[5] Jalaluddin, N. S. M., & Othman, R. Y. (2022). Perceptions on the challenges of banana cultivation and bio-based technology use among Malaysian smallholder farmers. Asian Journal of Agriculture and Development, 19(2), 25–33. https://doi.org/10.37801/ajad2022.19.2.3

[6] Sakthiganesh, M., &Dineshkumar, S. (2022). A study on constraints faced by the banana growers in the production and marketing of banana. EPRA International Journal of Agriculture and Rural Economic Research, 15–17. https://doi.org/10.36713/epra11651

[7] Jomanga, K. E. (2022). Review on broken-down resistance to diseases and its management; the hidden challenge in breeding and production of banana and plantains in developing countries. International Journal of Current Science Research and Review, 05(10). https://doi.org/10.47191/ijcsrr/v5-i10-17

[8] Balimwacha, M. E., Kambale, M. M., &Katembo, V. P. (2021). Constraints to banana (Musa spp) production in Beni territory of North-Kivu, Democratic Republic of Congo. African Journal of Agricultural Research, 17(5), 697–704. https://doi.org/10.5897/ajar2021.15453

[9] Adero, M., Tripathi, J. N., & Tripathi, L. (2023). Advances in somatic embryogenesis of banana. International Journal of Molecular Sciences, 24(13), 10999. https://doi.org/10.3390/ijms241310999

[10] Salokhe, M. R. (2023). Machine learning: Applications in agriculture (crop yield prediction, disease and pest detection). International Journal of Advanced Research in Science, Communication and Technology, 592–597. https://doi.org/10.48175/ijarsct-12088

[11] Salokhe, M. R. (2023). Machine Learning: Applications in Agriculture (Crop Yield Prediction, Disease and Pest Detection). International Journal of Advanced Research in Science, Communication and Technology, 7(7), 592–597.

[12] Saxena, D., Kaushik, D., Somvanshi, L., & Trivedi, S. (2023). FARMINGTON - A Machine Learning Approach in Agriculture. In 2023 International Conference on Computational Intelligence, Communication Technology and Networking (CICTN) (pp. 1–6).

[13] Banik, A., Patil, T., Vartak, P., & Jadhav, V. (2023). Machine Learning in Agriculture: A Neural Network Approach. In 2023 4th International Conference for Emerging Technology (INCET) (pp. 1–6).

[14] Tripathi, P., Kumar, N., Rai, M., Shukla, P. K., & Verma, K. N. (2023). Applications of Machine Learning in Agriculture. In Advances in Electronic Government, Digital Divide, and Regional Development (pp. 99–118).

[15] Bhuiyan, M. A. B., Abdullah, H. M., Arman, S. E., Rahman, S. S., & Al Mahmud, K. (2023). BananaSqueezeNet: A very fast, lightweight convolutional neural network for the diagnosis of three prominent banana leaf diseases. Smart Agricultural Technology, 4, 100214.

[16] Jadhav, S., Gandhi, S., Joshi, P., Choudhary, V., &Walunjkar, S. (2023). Banana Crop Disease Detection Using Deep Learning Approach. International Journal for Research in Applied Science and Engineering Technology, 11(5), 2061–2066.

[17] Mathew, D., Kumar, C. S., & Cherian, K. A. (2023). Classification of leaf spot diseases in banana using pre-trained convolutional neural networks. In 2023 International Conference on Control, Communication and Computing (ICCC) (pp. 1–6).

[18] Mahendran, T., & Seetharaman, K. (2023). Feature extraction and classification based on pixel in banana fruit for disease detection using neural networks. In Third International Conference on Advances in Electrical, Computing, Communication and Sustainable Technologies (ICAECT). https://doi.org/10.1109/icaect57570.2023.10117959

[19] S., A. N., R., H., S., R., Gaur, S., & R, S. (2023). A smart agriculturing IoT system for banana plants disease detection through inbuilt compressed sensing devices. Multimedia Tools and Applications, 82(29), 45519–45539. https://doi.org/10.1007/s11042-023-15442-6

[20] Subramani, S. S., Shakeel, M. P., Aboobaider, B. B. M., & Salahuddin, L. B. (2022). Classification learning assisted biosensor data analysis

  

for preemptive plant disease detection. ACM Transactions on Sensor Networks. https://doi.org/10.1145/3572775

[21] Sanga, S. (n.d.). Development of an early detection tool for banana diseases: A case of Mbeya and Arusha region. https://doi.org/10.58694/20.500.12479/1346

[22] Nandhini, A., R., H., S., R., G., & R, S. (2022). A smart agriculturing IoT system for banana plants disease detection through inbuilt compressed sensing devices. https://doi.org/10.21203/rs.3.rs-2182006/v1

[23] da Silva, A. C. B., Oliveira, F. G., & da F. G. P. Braga, R. N. (2023). Yield prediction in banana (Musa sp.) using STELLA model. Acta Scientiarum. Agronomy, 45, e58947. https://doi.org/10.4025/actasciagron.v45i1.58947

[24] Pandya, U., Mudaliar, A., & Gaikwad, A. (2023). Forecasting of banana crop productivity using geospatial approach: A case study of Anand District. ECWS-7 2023. https://doi.org/10.3390/ecws-7-14248

[25] Zhang, H., Zhang, Y., Li, X., Li, M., & Tian, Z. (2023). Predicting banana yield at the field scale by combining Sentinel-2 time series data and regression models. Applied Engineering in Agriculture, 39(1), 81–94. https://doi.org/10.13031/aea.15220

[26] Bakare, Y. B. (2023). Machine learning-based smart irrigation system and soil nutrients analysis to increase productivity in agriculture field. AIP Conference Proceedings. https://doi.org/10.1063/5.0116007

[27] Fedosov, A. Yu., &Menshikh, A. M. (2022). Implementation of artificial intelligence in agriculture to optimize irrigation. Agricultural Machinery and Technologies, 16(4), 45–53. https://doi.org/10.22314/2073-7599-2022-16-4-45-53

[28] Devan, K. P. K., Swetha, B., Sruthi, P. U., & Varshini, S. (2023). Crop yield prediction and fertilizer recommendation system using hybrid machine learning algorithms. In 2023 IEEE 12th International Conference on Communication Systems and Network Technologies (CSNT). https://doi.org/10.1109/csnt57126.2023.10134662

[29] G, P. B., K, T. D., & N, T. K. (2022). ML based methods XGBoost and Random Forest for crop and fertilizer prediction. In 14th International Conference on Computational Intelligence and Communication Networks (CICN). https://doi.org/10.1109/cicn56167.2022.10008234

[30] Aruna, M., Narayana, P. B., Kumar, S. N., Ala Walid, Md. A., Patra, J. P., & Kumar, B. S. (2023). Arithmetic optimization algorithm with machine learning based smart irrigation system in IoT environment. In 2023 Fifth International Conference on Electrical, Computer and Communication Technologies (ICECCT). https://doi.org/10.1109/icecct56650.2023.10179741

[31] Enríquez, J., & Macas, M. (2023). Artificial intelligence-based banana ripeness detection. Communications in Computer and Information Science, 197–211. https://doi.org/10.1007/978-3-031-24985-3_15

[32] Saranya, N., Srinivasan, K., & Kumar, S. K. P. (2023). FBCNN-TSA: An optimal deep learning model for banana ripening stages classification. Journal of Intelligent & Fuzzy Systems, 44(3), 5257–5273. https://doi.org/10.3233/jifs-221841

[33] [33] Baglat, P., Hayat, A., Mendonça, F., Gupta, A., Mostafa, S. S., & Morgado-Dias, F. (2023). Non-destructive banana ripeness detection using shallow and deep learning: A systematic review. Sensors, 23(2), 738. https://doi.org/10.3390/s23020738

[34] Mathew, M. B., Manjunathan, G. S., Gokul, B., Ganesh, K. M., Sajidha, S. A., & Nisha, V. M. (2023). Banana ripeness identification and classification using hybrid models with RESNET-50, VGG-16 and machine learning techniques. Lecture Notes in Electrical Engineering, 259–273. https://doi.org/10.1007/978-981-99-0085-5_22

[35] Almezhghwi, K., Algazewe, W., &Shwehdi, R. (2023). Using residual learning in the food processing sector: The case of banana sorting. Lecture Notes in Networks and Systems, 406–412. https://doi.org/10.1007/978-3-031-25252-5_54

[36] Duth, P. S., & Shashidhara, B. S. (2022). Banana grading using deep learning techniques. 2022 IEEE International Conference on Data Science and Information System (ICDSIS). https://doi.org/10.1109/icdsis55133.2022.9915998

[37] S, R., Ganguli, S., Selvan, P. T., Nayak, M. M., Chaudhury, S., Espina, R. U., & Ofori, I. (2022, May 23). Deep Learning Based Dual Channel Banana Grading System Using Convolution Neural Network. Journal of Food Quality, 2022, 1–9. https://doi.org/10.1155/2022/6050284Zhou et al. (2023). Advancement in artificial intelligence for on-farm fruit sorting and transportation. Frontiers in Plant Science, 14. https://doi.org/10.3389/fpls.2023.1082860

[38] Ackerson, J. P. (2022, August). Precision agriculture and soil health. Crops & Soils, 55(5), 35–39. https://doi.org/10.1002/crso.20214

[39] Shaheb, M. R., Sarker, A., & Shearer, S. A. (2022, December). Precision agriculture for sustainable soil and crop management. In Soil Science - Emerging Technologies, Global Perspectives and Applications. https://doi.org/10.5772/intechopen.101759

[40] Deone, J. B., Afreen, R. K., &Jadhao, V. R. (2023). Techniques applied to increase soil fertility in smart agriculture. In Intelligent Edge Computing for Cyber Physical Applications, 217–228. https://doi.org/10.1016/b978-0-323-99412-5.00008-3

[41] Senapaty, M. K., Ray, A., &Padhy, N. (2023). IoT-enabled soil nutrient analysis and crop recommendation model for precision agriculture. Computers, 12(3), 61. https://doi.org/10.3390/computers12030061

[42] S., A. N., R., H., S., R. S., Gaur, S., & R, S. (2023). A smart agriculturing IoT system for banana plants disease detection through inbuilt compressed sensing devices. Multimedia Tools and Applications, 82(29), 45519–45539. https://doi.org/10.1007/s11042-023-15442-6.

[43] Nandhini, A., R., H., S., G., & R, S. (2022). A Smart Agriculturing IoT System for Banana Plants Disease Detection through Inbuilt Compressed Sensing Devices. https://doi.org/10.21203/rs.3.rs-2182006/v1.

[44] Ahmad, M. N., Anuar, M. I., Abd Aziz, N., Mohd Bakri, M. A., Hashim, Z., & Abu Seman, I. (2022). Addressing functionalities of agricultural robotic (agribots) and automation in the agriculture practices: What's next? Advances in Agricultural and Food Research Journal, 4(1). https://doi.org/10.36877/aafrj.a0000298.

[45] Guo, J., Duan, J., Yang, Z., &Karkee, M. (2022). De-handing technologies for banana postharvest operations—Updates and challenges. Agriculture, 12(11), 1821. https://doi.org/10.3390/agriculture12111821.

[46] Bahadure, R. B., & Patel, M. (2018). Design and development of automated banana pruning machine. International Journal of Mechanical and Production Engineering Research and Development, 8(5), 375-384.

[47] Gopinath, S., & Sujatha, K. (2020). Application of drones in agriculture: A comprehensive review. Journal of Agriculture and Environmental Sciences, 9(1), 1-12.

[48] Lu, X., Wu, D., Qiao, C., & Pan, Y. (2019). An intelligent agricultural irrigation system based on Internet of Things. In 2019 IEEE 4th Advanced Information Technology, Electronic and Automation Control Conference (IAEAC) (pp. 1310-1314). IEEE.

[49] Ceballos, G. P., Gonzalez, P. S., & Boada, M. J. G. (2018). Application of machine learning in agriculture: A systematic review. Computers and Electronics in Agriculture, 153, 69-81.

[50] Kansal, A., Jain, A., & Gupta, P. (2021). Impact of climate change on agriculture: A review of the major challenges and adaptation strategies in banana cultivation. Journal of Agrometeorology, 23(2), 163-172.

[51] Zhdanovskaya, A., Baidakova, D., &Ustalov, D. (2023). Data labeling for machine learning engineers: Project-based curriculum and data-centric competitions. Proceedings of the AAAI Conference on Artificial Intelligence, 37(13), 15886–15893. https://doi.org/10.1609/aaai.v37i13.26886.

[52] Vidhya, G., Nirmala, D., & Manju, T. (2023). Quality challenges in deep learning data collection in perspective of artificial intelligence. Journal of Information Technology and Computing, 4(1), 46–58. https://doi.org/10.48185/jitc.v4i1.725.

[53] Bakaev, M., &Khvorostov, V. (2023). Quality of labeled data in machine learning: Common sense and the controversial effect for user behavior models. INTELS'22. https://doi.org/10.3390/engproc2023033003.

[54] Kara, N., et al. (2022). A SHAP-based active learning approach for creating high-quality training data. 2022 IEEE International Conference on Big Data (Big Data). https://doi.org/10.1109/bigdata55660.2022.10020327.

[55] Kara, N., et al. (2022). A SHAP-based active learning approach for creating high-quality training data. 2022 IEEE International Conference on Big Data (Big Data). https://doi.org/10.1109/bigdata55660.2022.10020327.

[56] Abdaljalil, S., Hassanein, S., Mubarak, H., & Abdelali, A. (2023). Towards generalization of machine learning models: A case study of Arabic sentiment analysis. Proceedings of the International AAAI Conference on Web and Social Media, 17, 971–980. https://doi.org/10.1609/icwsm.v17i1.22204.

[57] Shultzman, A. (2023). Generalization and estimation error bounds for model-based neural networks. arXiv.org. https://arxiv.org/abs/2304.09802

[58] Wang, M., Wang, B., Zhang, R., Wu, Z., & Xiao, X. (2023). Flexible Vis/NIR wireless sensing system for banana monitoring. Food Quality and Safety, 7. https://doi.org/10.1093/fqsafe/fyad025.

[59] Pragadeswaran, S., Vishnu, S., Surya, V., Kurup, V., & Tamilselvan, S. (2023). An investigation on real-time monitoring system for livestock and agriculture using IoT. International Journal of Advanced Research in Science, Communication and Technology, 102–109. https://doi.org/10.48175/ijarsct-8566.

[60] Khan, R., Khan, A., Murshad, I., Shaikh, A., &Dahatonde, N. (2022). Real-time monitoring based smart farming. Journal of Cyber Security in Computer System, 1(1), 33–41. https://doi.org/10.46610/jcscs.2022.v01i01.005.

[61] Gandhi, S., & Shah, A. (2021). Continuous monitoring of banana plantations. Advances in Intelligent Systems and Computing, 403–413. https://doi.org/10.1007/978-981-16-2123-9_31.

[62] Wolf, M., et al. (2022). Real-time locating systems for human-centered production planning and monitoring. IFAC-PapersOnLine, 55(2), 366–371. https://doi.org/10.1016/j.ifacol.2022.04.221.

[63] Adilova, L., Kamp, M., Andrienko, G., &Andrienko, N. (2023). Re-interpreting rules interpretability. International Journal of Data Science and Analytics, Published. https://doi.org/10.1007/s41060-023-00398-5

[64] Gao, L., & Guan, L. (2023). Interpretability of Machine Learning: Recent Advances and Future Prospects. *IEEE MultiMedia, 30*(4), 105–118. https://doi.org/10.1109/mmul.2023.3272513

[65] Liu, W. (2023). IoT-based multi-channel information integration method for wireless sensor networks. *Proceedings of the Indian National Science Academy, 89*(3), 705–714. https://doi.org/10.1007/s43538-023-00185-7

[66] Singh, S., Sharma, M., Heard, J., Lew, J. D., Saber, E., & Markopoulos, P. P. (2023). Multimodal aerial view object classification with disjoint unimodal feature extraction and fully connected-layer fusion. Big Data V: Learning, Analytics, and Applications, Published. https://doi.org/10.1117/12.2664041

[67] Xu, Y., & Hayat, S. (2023). MASIv2 enables standardization and integration of multi-modal single-cell and spatial omics data with one general framework. Published, https://doi.org/10.1101/2023.05.15.540808

[68] Hafner, S. (2023). Multi-Modal Deep Learning for Multi-Temporal Urban Mapping With a Partly Missing Optical Modality. arXiv.org. https://arxiv.org/abs/2306.00640

[69] Xiao, M., Hu, C., & Wu, Z. (2023). Transfer Learning-Based Modeling and Predictive Control of Nonlinear Processes. 2023 American Control Conference (ACC), Published. https://doi.org/10.23919/acc55779.2023.10156613

[70] Chen, Z.-C., et al. (2023). How to Estimate Model Transferability of Pre-Trained Speech Models? Aug. 20, https://doi.org/10.21437/interspeech.2023-1079

[71] Subramanian, S. (2023). Towards Foundation Models for Scientific Machine Learning: Characterizing Scaling and Transfer Behavior. arXiv.org. https://arxiv.org/abs/2306.00258

[72] Liu, T., Ni, S., Li, X., Zhu, Y., Kong, L., & Yang, Y. (2023). Deep Reinforcement Learning Based Approach for Online Service Placement and Computation Resource Allocation in Edge Computing. *IEEE Transactions on Mobile Computing, 22*(7), 3870–3881. https://doi.org/10.1109/tmc.2022.3148254

[73] Han, Y., Liang, J., & Lin, Y. (2023). Joint Deployment Optimization of Parallelized SFCs and BVNFs in Multi-Access Edge Computing. *Applied Sciences, 13*(12), 7261. https://doi.org/10.3390/app13127261

[74] Thalpage, N. (2023). Unlocking the Black Box: Explainable Artificial Intelligence (XAI) for Trust and Transparency in AI Systems. *Journal of Digital Art & Humanities, 4*(1), 31–36. https://doi.org/10.33847/2712-8148.4.1_4

[75] Byeon, H., &Shaheema, S. B. (2023). Explainable AI: Techniques and Tools for Interpreting Deep Learning Models. Cutting-Edge Technologies in Innovations in Computer Science and Engineering, Published. https://doi.org/10.59646/csebookc10/004

[76] Feldkamp, N., & Strassburger, S. (2023). From Explainable AI to Explainable Simulation: Using Machine Learning and XAI to understand System Robustness. ACM SIGSIM Conference on Principles of Advanced Discrete Simulation, Published. https://doi.org/10.1145/3573900.3591114

[77] Rossoni, A. L., de Vasconcellos, E. P. G., & de Castilho Rossoni, R. L. (2023). Barriers and facilitators of university-industry collaboration for research, development and innovation: a systematic review. Management Review Quarterly,Published. https://doi.org/10.1007/s11301-023-00349-1

[78] Zhou, X., Ma, W., Zheng, H., Li, J., & Zhu, H. (2023). Promoting banana farmers’ adoption of climate-smart agricultural practices: the role of agricultural cooperatives. Climate and Development, 1–10. https://doi.org/10.1080/17565529.2023.2218333

[79] Pulford, J., et al. (2023). How international research consortia can strengthen organizations’ research systems and promote a conducive environment and culture. *BMJ Global Health, 8*(4), e011419. https://doi.org/10.1136/bmjgh-2022-011419

[80] Hardie Hale, E., Jadallah, C. C., & Ballard, H. L. (2021). Collaborative research as boundary work: Learning between rice growers and conservation professionals to support habitat conservation on private lands. *Agriculture and Human Values, 39*(2), 715–731. https://doi.org/10.1007/s10460-021-10283-1

[81] Quintero, S., Giraldo, D. P., & Garzon, W. O. (2022). Analysis of the Specialization Patterns of an Agricultural Innovation System: A Case Study on the Banana Production Chain (Colombia). *Sustainability, 14*(14), 8550. https://doi.org/10.3390/su14148550

[82] Sahu, P., Singh, A. P., Chug, A., & Singh, D. (2022). A Systematic Literature Review of Machine Learning Techniques Deployed in Agriculture: A Case Study of Banana Crop. IEEE Access, 10, 87333–87360. https://doi.org/10.1109/access.2022.3199926

[83] Olivares, B. O., et al. (2022). Prediction of Banana Production Using Epidemiological Parameters of Black Sigatoka: An Application with Random Forest. *Sustainability, 14*(21), 14123. https://doi.org/10.3390/su142114123

[84] Athiraja, A., & Vijayakumar, P. (2020). RETRACTED ARTICLE: Banana disease diagnosis using computer vision and machine learning methods. *Journal of Ambient Intelligence and Humanized Computing, 12*(6), 6537–6556. https://doi.org/10.1007/s12652-020-02273-8

[85] Ramezanpour, M. R., &Farajpour, M. (2022). Application of artificial neural networks and genetic algorithm to predict and optimize greenhouse banana fruit yield through nitrogen, potassium and magnesium. *PLOS ONE, 17*(2), e0264040. https://doi.org/10.1371/journal.pone.0264040

[86] Boddupalli, B. M., & Singh, O. N. (2021). Machine learning-based banana diseases detection and classification: A review. Computers and Electronics in Agriculture, 181, 105984. https://doi.org/10.1016/j.compag.2020.105984

[87] Thakur, N. S., et al. (2019). An artificial intelligence-based predictive model for banana yield forecasting. Computers and Electronics in Agriculture, 157, 417-425. https://doi.org/10.1016/j.compag.2018.12.012

  

[88] Ahmed, B., et al. (2020). An intelligent precision agriculture system for banana cultivation. Computers and Electronics in Agriculture, 170, 105273. https://doi.org/10.1016/j.compag.2019.105273

[89] Jayasundara, J. M. R. A. C., et al. (2020). Machine learning applications in optimizing banana ripening conditions. *Journal of Food Science and Technology, 57*(2), 513-521. https://doi.org/10.1007/s13197-019-04056-7

[90] Tripathi, S., et al. (2018). Predicting banana yield using machine learning algorithms. *Journal of Agrometeorology, 20*(1), 56-60.

[91] Mishra, A., Padhee, A. K., & Sarangi, S. K. (2019). Disease and pest forecasting in banana using machine learning techniques: A review. *International Journal of Current Microbiology and Applied Sciences, 8*(3), 2428-2438.

[92] Khan, M. S., et al. (2021). Machine learning-based intelligent irrigation management system for banana cultivation. Computers and Electronics in Agriculture, 181, 105924. https://doi.org/10.1016/j.compag.2020.105924

[93] Kumar, A., et al. (2017). Predictive modeling of soil properties using machine learning algorithms for banana cultivation. Computers and Electronics in Agriculture, 142, 511-518. https://doi.org/10.1016/j.compag.2017.10.031

[94] Patel, V., Khan, R. M., & Trivedi, A. I. (2020). Machine learning-based real-time disease detection in banana plants. *International Journal of Recent Technology and Engineering, 8*(6), 3008-3011.

[95] Silva, J., et al. (2020). Predicting Banana Yield Using Machine Learning Techniques: A Case Study in Brazil. *IEEE Latin America Transactions, 18*(11), 2189-2196. https://doi.org/10.1109/TLA.2020.9182283

[96] Sharma, S., Dubey, A., & Kumar, S. (2021). Machine Learning-Based Pest and Disease Management in Banana Plantations: A Review. *International Journal of Current Microbiology and Applied Sciences, 10*(6), 689-698. https://doi.org/10.20546/ijcmas.2021.1006.081

[97] Yang, C., et al. (2019). Banana Leaf Disease Detection Based on Deep Learning. *International Journal of Agricultural and Biological Engineering, 12*(2), 131-137. https://doi.org/10.25165/j.ijabe.20191202.4632

[98] Bhuiyan, M. A. B., et al. (2023). BananaSqueezeNet: A very fast, lightweight convolutional neural network for the diagnosis of three prominent banana leaf diseases. Smart Agricultural Technology, 4, 100214. https://doi.org/10.1016/j.atech.2023.100214

[99] Magno, R. D. C., Bersamen, P. J. S., & Valiente, L. D. (2022). Monitoring of Banana Ripening Process and Identification of Banana type using FRCNN, LSTM, And Color Segmentation. 2022 IEEE 14th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment, and Management (HNICEM), Published. https://doi.org/10.1109/hnicem57413.2022.10109517

[100] Mahendran, T., & Seetharaman, K. (2023). Feature Extraction and Classification Based on Pixel in Banana Fruit for Disease Detection Using Neural Networks. 2023 Third International Conference on Advances in Electrical, Computing, Communication and Sustainable Technologies (ICAECT), Published. https://doi.org/10.1109/icaect57570.2023.10117959

  