Optimizing Lettuce Cultivation: Nutrient And Disease Monitoring In Vertical Farms

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Abstract

Plant health management in vertical farming can undergo a revolution through the utilization of artificial intelligence (AI) and computer vision for real-time detection of nutrient deficiencies and diseases in lettuce plants. To tackle this challenge, this study delves into state-of-the-art convolutional neural network (CNN) models, encompassing VGG16, VGG19, ResNet50, EfficientNetB0, MobileNetV3, and Xception. These models underwent meticulous training and fine-tuning, harnessing transfer learning techniques to heighten accuracy and convergence despite limited data.

The significance of this endeavor lies in its capacity to elevate and refine vertical farming practices. Manual assessment of plant health proves labor-intensive and error-prone, impinging on yield and resource efficiency. By automating diagnostics via AI-driven models, this work aspires to alleviate these hurdles and optimize crop production. This study's dataset encompasses an all-encompassing array of lettuce images, capturing diverse health conditions, nutrient scarcities, and disease indications.

The methodological approach adopted here guarantees reproducibility by illuminating model selection, training protocols, and dataset curation. The study unveils findings that underscore the precision and resilience of AI-based diagnostics. The seamless integration of these models into vertical farming systems could potentially chart the course for sustainable and robust crop cultivation, curtailing losses and maximizing yields through well-timed interventions.

Keywords: *Artificial Intelligence (AI), Vertical Farming, Real-time Diagnosis, Nutrient Deficiency, Disease Detection, Lettuce Plants, Convolutional Neural Networks (CNNs), Crop Health Monitoring, Sustainable Crop Production.*

I. INTRODUCTION

Vertical farming stands at the forefront of a transformative paradigm shift in modern agriculture. It offers innovative solutions to the pressing global challenges of food production by revolutionizing the way we utilize space, conserve water resources, and enable sustainable urban cultivation. Within this landscape, harnessing advanced technologies is not just a choice but an imperative, as they hold the key to optimizing crop management in vertical farming systems.

One of the most critical challenges that vertical farming endeavors to address is the real-time monitoring and management of crop health, specifically, the timely detection of nutrient deficiencies and diseases. These aspects are foundational to sustaining optimal crop growth and maximizing yields. Conventional manual monitoring methods, however, are fraught with limitations. They are inherently time-consuming, labor-intensive, and susceptible to human errors, which can be particularly detrimental when it comes to identifying subtle signs of malnutrition or the early stages of diseases.

In response to these formidable challenges, this study embarks on a pioneering journey by exploring the seamless integration of artificial intelligence (AI) into the realm of vertical farming. Our focus centers on lettuce plants, a staple crop within vertical farming systems, as a representative case study. We aim to investigate the feasibility and efficacy of AI-powered computer vision models to perform rapid, precise, and automated identification of nutrient deficiencies and diseases in lettuce.

Central to our research is the development and utilization of a comprehensive and diverse dataset. This dataset meticulously captures the multifaceted spectrum of lettuce conditions, encompassing various classes that include Fully Nutritional, Nitrogen Deficient, Phosphorus Deficient, Potassium Deficient, Downy Mildew, Growing, Health, Raising Seeding, and Sclerotinia Rot. This diversity ensures that our AI models are not only trained on a wide range of scenarios but also capable of effectively discerning between these intricate health states.

To tackle the intricate task of nutrient deficiency and disease classification, we have painstakingly selected state-of-the-art AI models. Specifically, our study focuses on VGG16, VGG19, ResNet50, EfficientNetB0, MobileNetV3, and Xception. These models stand out not just for their prowess in image classification but also for their adaptability in various deployment scenarios, ranging from cloud systems to resource-constrained edge devices. Our methodology places a strong emphasis on data collection and augmentation techniques, which play a pivotal role in enhancing the efficacy of model training. The meticulous selection and training process have yielded remarkable accuracies, setting the stage for the AI-powered revolution in vertical farming.

Furthermore, our commitment to excellence extends to the technological infrastructure employed in this research. The integration of an NVIDIA GPU into our model training processes has significantly expedited training times, enhancing both scalability and cost-efficiency. This technological synergy ensures that our AI models are not only highly accurate but also practical and feasible for real-world deployment.

In the sections that follow, we will delve deeper into our experimental findings and outcomes. These insights are not just confined to the realm of academic inquiry; they carry profound implications for the future of vertical farming. The transformative potential of AI-driven diagnostics, as demonstrated in our study, has the power to reshape the very landscape of vertical farming. These AI-powered tools enable proactive and precise management of crop health, ensuring timely interventions, targeted nutrient delivery, and, ultimately, the optimization of crop yields.

The research presented here contributes to the burgeoning body of work that leverages AI to optimize agricultural practices. Beyond the confines of academia, our study holds the potential to reshape the trajectory of vertical farming, addressing critical concerns surrounding food security and sustainability.

II. LITERATURE REVIEW

The utilization of Convolutional Neural Network (CNN) models in datasets pertaining to vertical farming and lettuce production has been a focal point of extensive exploration within the academic literature. Zhang et al. conducted a seminal study that exemplified the potential of CNN models. They harnessed these models using digital photographs of three distinct lettuce species to establish a robust connection between images and essential growth-related variables, including but not limited to leaf fresh weight (LFW), leaf dry weight (LDW), and leaf area (LA) [1]. This groundbreaking research not only underscored the capability of CNN models to estimate growth-related features but also laid the foundation for automated and accurate assessments in lettuce cultivation.

Expanding upon this foundation, Hwang et al. introduced the groundbreaking concept of pseudo-crop mixing. This innovative machine-based monitoring system was explicitly designed to automate the meticulous task of vertical farm monitoring while simultaneously enhancing measurement accuracy. The authors of this pioneering work developed a Mask R-CNN model, with the unified ResNet50-FPN serving as the backbone architecture—just one of the six models thoughtfully employed in this study [2]. Their findings added a critical layer to the literature by illuminating the remarkable effectiveness of deep learning models in calculating crop area and monitoring growth within vertical farming systems. The implications of such automated precision are profound, promising to streamline crop management practices while ensuring resource optimization.

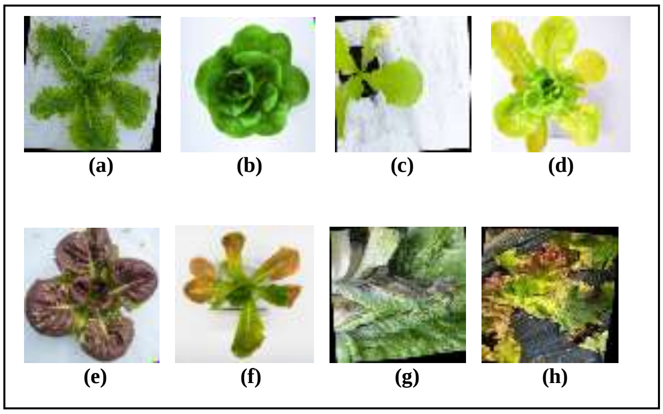
Moreover, the application of deep learning techniques in lettuce growth monitoring extends beyond the realm of growth-related features. Gang, Kim, and Kim took an innovative step by employing a CNN-based model to monitor a diverse array of growth indices. These encompassed not only fundamental metrics like shoot fresh weight and shoot dry weight but also more intricate measurements such as height, leaf area, and diameter across four greenhouse lettuce varieties—Lugano, Salanova, Aphylion, and Satine—within a greenhouse hydroponics system [3]. The complexity of this study, evident in its two-stage development process utilizing ResNet50V2 layers, illuminates the adaptability of CNN models for a myriad of growth-related metrics in lettuce cultivation. This holistic approach to growth monitoring promises a more comprehensive understanding of lettuce health and performance, contributing significantly to the lettuce production literature.

Deep learning and artificial intelligence (AI) have also proven to be potent tools in the detection of physical anomalies in lettuce crops. Hamidon and Ahamed embarked on a mission that involved the utilization of 2333 meticulously enhanced photos of lettuce plants captured under specific settings. They skillfully constructed a tip-burn detection system leveraging three distinct one-stage detectors—CenterNet, YOLOv4, and YOLOv5 [4]. The results of their research offer a substantial contribution to the literature by highlighting the potential of AI in addressing one of the most pressing concerns in lettuce production—tip burn. This work not only demonstrates the ability to detect physical anomalies with precision but also emphasizes the practicality of utilizing AI for such critical tasks.

Similarly, Osorio et al. made significant strides in the utilization of multispectral images collected through a hyperspectral camera to train deep learning-based techniques for weed estimation in lettuce crops. Their methodological arsenal included Support Vector Machines (SVM) employing Histograms of Oriented Gradients (HOG) as feature descriptors, YOLOV3, and Mask R-CNN. Notably, the latter offered instance segmentation for individual weeds—an invaluable capability in weed management [5]. The incorporation of a normalized difference vegetation index (NDVI) for background subtraction further heightened the effectiveness of these methods. This work, situated at the intersection of AI and agriculture, illustrates not only the potential for weed management but also the adaptability of AI techniques to diverse agricultural challenges.

Lastly, Hu et al. brought AI to the forefront of disease detection in lettuce crops. Their innovative approach, centered on utilizing photos from a lettuce field in Tongzhou District, Beijing, China, resulted in the development of a robust disease detection system. They harnessed four state-of-the-art multi-object tracking (MOT) models—ByteTrack, ByteTrack with NSA Kalman filter, FairMOT, and SORT [6]. These models were carefully fine-tuned using default hyperparameters on the dataset, culminating in a promising technique for disease detection in lettuce crops. The implications of this work are far-reaching, promising to revolutionize disease management in lettuce cultivation and ensuring healthier and more productive crops.

Collectively, an in-depth examination of these studies within the literature underscores the profound impact of deep learning and AI on various facets of vertical farming and lettuce production. These advancements have ushered in new opportunities for automated monitoring, accurate growth estimation, and the identification of physical anomalies and infections. These achievements are instrumental in promoting more efficient, sustainable, and resilient lettuce cultivation practices. However, it's essential to acknowledge that these are not isolated victories; they represent the ongoing and evolving relationship between AI and agriculture. The future holds the promise of even more refined and adaptable AI solutions that can revolutionize the landscape of lettuce production, addressing food security concerns on a global scale.



With that said, the work presented in this study, which demonstrates the capacity of deep learning and AI to detect nutrient deficiencies, diseases, and physical anomalies in lettuce, using models adaptable to diverse scenarios, is a testament to the transformative potential of AI in agriculture. Whether deployed in real-time within vertical farms or through cloud applications for crop monitoring, the fusion of AI and agriculture stands at the forefront of innovation, poised to redefine the future of sustainable and data-driven lettuce cultivation practices. This synergistic approach between technology and agriculture not only enhances productivity but also holds the key to addressing global food security challenges and fostering ecological equilibrium.

III. Materials and Methods

A. Data Collection

During the data collection phase, an extensive process was undertaken to curate a comprehensive and diverse dataset, forming the cornerstone for training the AI models in this study. The dataset amalgamated nutrient deficiency data [7], initially encompassing four image classes—Fully Nutritional, Nitrogen Deficient, Phosphorus Deficient, and Potassium Deficient—and disease data [8], initially containing five image classes—Downy Mildew, Growing, Health, Raising Seeding, and Sclerotinia Rot. Following preprocessing, the dataset was refined to comprise eight distinct image classes: Downy Mildew (DM), Growing Good (GG), Grown and Healthy (GH), Nitrogen Deficient (ND), Phosphorus Deficient (PD), Potassium Deficient (KD), Sclerotinia Rot (SR), and Seedling (S). The amalgamation aimed to eliminate duplications and ensure that the AI models could accurately discern diverse classes.

B. Data Augumentation

To address the limited availability of data and enhance the generalizability of the AI models, data augmentation techniques were employed on the nutrient deficiency dataset. Each class of images was subjected to augmentation processes, including division into four sections and rotation by 90° and 180°. The disease dataset was cleaned by removing irrelevant and low-quality images. Regarding the combined dataset, the number of images in each of the eight classes was balanced. Overall, these techniques aimed to increase the data's size and diversity, enabling better model performance during the training phase. The total number of images for each class in the combined dataset can be seen in TABLE I.

C. Model Selection

Thoroughly selecting suitable AI models was essential for developing reliable and deployable AI solutions. After an extensive investigation and analysis of numerous criteria, including deployment settings and application situations, six cutting-edge CNN deep learning models specialized in image classification were chosen: VGG16, VGG19, ResNet50,

Fig 1 - Sample Images from the Dataset. (a) Growing Good, (b) Grown and Healthy, (c) Seedling, (d) Nitrogen Deficient, (e) Phosphorus Deficient, (f) Potassium Deficient, (g) Downy Mildew, (h) Sclerotinia Rot

TABLE I IMAGES IN THE DATASET

Class Name	GH	GG	S	ND
Total Images	240	408	398	232
Class Name	PD	KD	DM	SR

Total Images	252	288	374	403

Total images of each class in the final dataset after applying the data augmentation techniques

TABLE II TRAIN, TEST, AND VALIDATION SETS

Class Name	GH	GG	S	ND	PD	KD	DM	SR
Train Images	180	306	298	174	189	215	280	302
Test Images	24	40	40	23	25	29	37	40
Valid Images	36	62	60	35	38	44	57	61

Images in each of the classes after the train, test, and validation splits

EfficientNetB0, MobileNetV3, and Xception. These models were selected due to their particular image classification abilities and flexibility in a range of computational and inference settings

D. Model Training

The selected AI models underwent training using the compiled dataset, with a primary focus on refining pre-trained models for precise categorization of lettuce plants. A series of experiments were conducted to achieve high accuracy, involving adjustments to the number of trainable layers, batch sizes, optimizers, as well as the incorporation of dropout and dense layers. This iterative training strategy was adopted to enhance the proficiency of each model in recognizing and classifying nutrient deficiencies and diseases. The data was divided into training, validation, and test subsets at a ratio of 75%, 10%, and 15%, respectively. The distribution of images among these subsets across the eight classes of the amalgamated dataset is depicted in TABLE II.

E. Validation and Testing

After model training, the validation and testing steps were carried out to assess the performance and generalizability of the AI models. A validation dataset was used to verify the models' accuracies and ensure they were not overfitting the training data. The best weights of each model were saved during the training process through early stopping and callback checkpoints, monitored by validation loss. The models were then tested on a separate test dataset to determine their capacity to reliably diagnose nutrient deficiencies and diseases in real-world circumstances; the resulting accuracies are discussed in the Results section.

TABLE III HYPERPARAMETERS

Model Name	Trainable Layers	Optimizer	Batch Size & Dropout	Trainable Parameters
VGG16	2	Adam – 1 x 10^{-4}	64 & 0.2	109,520,628

VGG19	3	Adam – 1 x 10^{-4}	64 & 0.2	111,880,436
ResNet50	0	SGD – 1 x 10^{-2}	64	566,216
EfficientNetB0	16	Adam – 1 x 10^{-4}	64 & 0.2	17,229,464
MobileNet	3	Adam – 1 x 10^{-4}	64	3,158,024
Xception	7	Adam – 1 x 10^{-4}	64 & 0.2	5,307,272

Finalized hyperparameters for the six CNN models after being trained on different values

Fig 2. Block diagram of VGG16 indicating the trainable layers

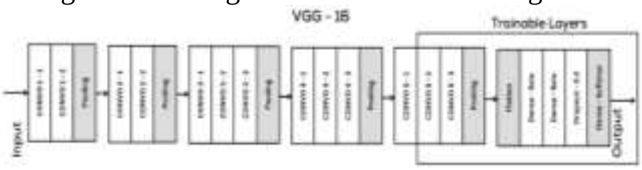


Fig 3. Block diagram of VGG19 indicating the trainable layers

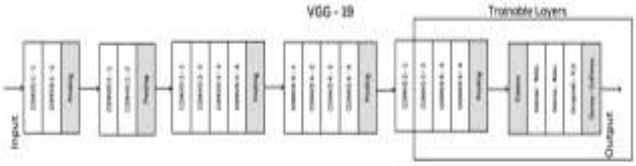
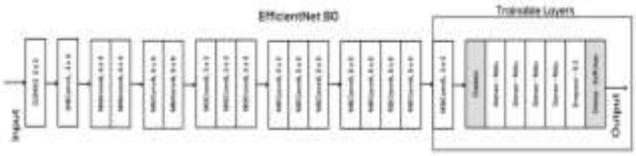


Fig 4S. Block diagram of EfficientNetB0 indicating the trainable layers



The finalized hyperparameters, along with the employed trainable layers and used optimizers, are summarized in TABLE III. The trainable layers indicate only the number of pre-trained layers that were retrained on the dataset, while the fully connected layers were entirely trained on the features extracted by the pre-trained layers on the dataset. The trainable layers of the VGG16, VGG19, and EfficientNetB0 models are illustrated in Fig 1, Fig 2, and Fig 3, respectively. As seen in TABLE III, dropout was not used for the ResNet50 and MobileNetV3 models. The dropout mentioned in the table applies only to fully connected layers, not to the pre-trained layers.

IV. Results

The results of the experiments described earlier demonstrate the effectiveness of the selected AI models in accurately detecting and classifying nutrient deficiencies and diseases in lettuce plants. Each model's performance was evaluated based on overall accuracy and individual class accuracies, as detailed by the following bullet points and TABLE IV:

- **VGG16**: The VGG16 model achieved an impressive overall accuracy of approximately 96%. Among the nutrient deficiency and disease classes, it displayed notable accuracies for most classes, demonstrating its proficiency in lettuce plant classification.
- **VGG19**: The VGG19 model achieved an overall accuracy of approximately 91%. While slightly lower than VGG16, it still demonstrated commendable performance in differentiating between nutrient deficiencies and diseases in lettuce plants.
- **ResNet50**: The ResNet50 model delivered an overall accuracy of approximately 96%, on par with VGG16. Its ability to accurately classify lettuce plants' health conditions reinforces its suitability for vertical farming applications.
- **EfficientNetB0**: The EfficientNetB0 model showcased an impressive overall accuracy of approximately 97%. Its lightweight yet powerful architecture contributed to its high performance in nutrient deficiency and disease classification.
- **MobileNetV3:** The MobileNetV3 model also demonstrated strong performance, achieving an overall accuracy of approximately 96.5%. Its notable accuracy reaffirms its potential as a valuable addition to the suite of AI models for lettuce plant classification in vertical farming.
- **Xception**: The Xception model emerged as the top performer, achieving an overall accuracy of approximately 99%. Its notable accuracy across classes highlights its potential for precise and reliable monitoring in vertical farming, making it suitable for real-time deployment in edge devices due to its small size.

These results indicate that the AI models, particularly the EfficientNetB0, MobileNetV3, and Xception models, exhibit strong potential to be integrated into real-world vertical farming systems. By leveraging AI, vertical farmers can gain valuable insights into their crop health, enabling timely

TABLE IV ACCURACY

Class/Model	**VGG16**	**VGG19**	**ResNet50**
GH	100	86.11	100
GG	96.77	98.39	100
S	96.67	98.33	96.67
ND	97.12	94.29	100
PD	100	100	100
KD	100	81.82	97.73
DM	96.5	87.72	94.74
SR	86.89	83.61	85.25
Total	**96.78**	**91.28**	**96.8**
Class/Model	**EfficientNetB0**	**MobileNetV3**	**Xception**
GH	100	100	100
GG	96.77	100	100
S	100	98.33	100
ND	94.29	100	100
PD	97.37	94.74	100
KD	100	93.18	97.73
DM	96.49	92.98	98.25
SR	91.8	96.72	95.1
Total	**97.09**	**96.98**	**98.88**

Accuracy score in % obtained by each of the models on all the classes of the test set.

interventions and optimized nutrient delivery to ensure maximum yields and minimal losses. Furthermore, the high accuracy rates achieved by these models underscore their significance in developing autonomous monitoring and management systems in vertical farming.

It's important to acknowledge that while the AI models demonstrated precise accuracy of over 90% for all models, there may be room for further improvements. Fine-tuning the models and expanding the dataset with additional classes and diverse samples could enhance their performance and robustness in real-world vertical farming scenarios.

Overall, these results validate the potential of AI in transforming vertical farming, paving the way for data-driven, efficient, and eco-friendly agricultural practices. The successful implementation of AI-driven crop monitoring and management systems has the potential to significantly improve crop health, reduce resource wastage, and contribute to global food security. Continued research and innovation in this field will lead to even more advanced AI solutions that can revolutionize the future of sustainable agriculture.

V. DISCUSSION

The integration of AI into vertical farming, as illustrated by the findings in this study, marks a significant turning point in the trajectory of agriculture. The exceptional performance showcased by the chosen AI models – VGG16, VGG19, ResNet50, EfficientNetB0, MobileNetV3, and Xception – for the detection of nutrient deficiencies and diseases within lettuce plants heralds the dawn of a new era in precision farming. These formidable AI-driven solutions not only augment the precision of crop monitoring but also open the door to a range of benefits, including improved resource efficiency, reduced environmental impact, and amplified crop yields. These outcomes collectively chart a path toward more sustainable and productive agriculture.

The cornerstone of our study's success lies in the diversity and complexity of the dataset we meticulously curated. Combined with extensive data augmentation and precise model fine-tuning, this dataset has been instrumental in shaping AI models that are exceptionally resilient and adaptable. The accuracy rates achieved by these models serve as a compelling testament to the transformative potential of AI in vertical farming. Such precision empowers growers with the ability to make timely interventions, administer nutrients with precision, and proactively manage crops, all of which are pivotal factors in maintaining crop health and mitigating losses.

Moreover, the incorporation of lightweight yet potent AI models, such as EfficientNetB0, MobileNetV3, and Xception, introduces practical advantages for deployment in resource-limited contexts. These models offer seamless integration into edge devices, cloud systems, and applications, effectively lowering barriers to entry and paving the way for extensive utilization across a wide spectrum of vertical farming setups. This adaptability is crucial, particularly in resource-constrained agricultural settings, where streamlined technology solutions can make a significant difference.

While our study underlines the immense potential of AI in agriculture, it also underscores the ongoing imperative for innovation and exploration in this field. The journey toward perfection is never truly complete, and the realm of AI in agriculture is no exception. To further enhance the precision and robustness of AI models, there is a compelling need for continuous refinement. This includes fine-tuning the AI models, expanding the dataset to encompass a broader array of classes and variations, and exploring novel approaches to data augmentation. These steps are essential to ensure that AI models remain at the forefront of agricultural innovation.

It's crucial to recognize that deploying AI models in real-world agricultural scenarios may introduce a new set of challenges. Issues related to computational resources, scalability, and data security must be approached with diligence and addressed comprehensively. As the adoption of AI in agriculture continues to grow, collaborative efforts among researchers, practitioners, and policymakers will play a pivotal role in developing frameworks and solutions that ensure the responsible and effective use of AI technology.

In conclusion, the integration of AI into vertical farming represents a landmark achievement with far-reaching implications for the future of agriculture. The remarkable performance of AI models in this study underscores the transformative potential of AI in enhancing precision, sustainability, and productivity in crop cultivation. As we navigate this new era of AI-powered agriculture, we must remain committed to continuous innovation, responsible deployment, and collaboration across disciplines. Together, we can harness the full potential of AI to revolutionize farming practices and address pressing global food security challenges.

VI. CONCLUSION

In summary, this research underscores the transformative potential of AI when harnessed in conjunction with vertical farming, heralding a paradigm shift in agriculture that transcends traditional practices. Through the integration of AI-powered tools, this study has vividly demonstrated the remarkable precision attainable in detecting nutrient deficiencies and diseases within lettuce plants, effectively revolutionizing the landscape of agricultural surveillance and management. The pivotal role played by AI models, including EfficientNetB0, MobileNetV3, and Xception, cannot be overstated. These models offer more than mere automation; they provide accurate, data-driven solutions that empower vertical farmers to embrace sustainable and eco-friendly practices.

The significance of this advancement extends far beyond the realm of lettuce cultivation, encompassing the entire agricultural landscape. AI-powered systems hold the potential to reshape the global food supply chain, rendering it more resilient, efficient, and adaptable in a dynamic world. Beyond sheer efficiency, AI's influence transcends the boundaries of lettuce production in vertical farming, venturing into uncharted territories of culinary innovation and crop longevity.

A compelling illustration of this transformative potential emerges from the pioneering work of Hamilton Horne, who has effectively harnessed AI to enhance his farming operations. Horne's innovative use of AI has enriched the culinary business by supplying chefs with fresher, longer-lasting, and more highly valued produce through containerized vertical farming, exemplified by Freight Farms' Greenery S. This innovation, encompassing a mere 320 square feet, yields an output comparable to 2.5 acres of traditional agriculture, effectively democratizing farming accessibility. Through AI, Horne has addressed long-standing concerns related to produce quality and waste in the culinary industry, setting a precedent for others to follow [9].

However, the latent potential of AI in vertical farming remains largely untapped. Visionary vertical farmers like Horne envision a future characterized by comprehensive automation through further integration of AI technology. Such advancements will not only relieve operational burdens but also elevate overall productivity and sustainability. AI-driven systems possess the capability to continuously monitor and optimize environmental conditions within vertical farms, ensuring the precise provisioning of light, water, and nutrients throughout crop growth stages. Machine learning algorithms will forecast optimal harvesting periods, thereby minimizing waste and significantly augmenting crop output.

Moreover, AI-enabled recipe generation, accounting for seasonal crop availability and nutritional needs, holds the promise of innovative, sustainable cuisines tailored to consumer preferences. This would not only enhance the culinary experience but also contribute to more efficient resource utilization.

The integration of AI into vertical farming has already demonstrated significant potential, as illustrated by Hamilton Horne's impactful AI implementation in Greenery S. However, the journey has only just begun. The trajectory of future research should be firmly rooted in refining and expanding AI applications, fostering extensive automation, personalized recipe generation, and sustainable crop management. This pursuit represents the realization of AI's vast potential in agriculture and the culinary sector alike.

Collaboration between AI researchers, vertical farmers, and culinary experts can usher in an era of efficient, eco-friendly, and delectable food production and consumption. As evident from the results presented in TABLE IV, showcasing performance exceeding 95%, the horizons of AI in vertical farming are broadened. With this goal in sight, the realm of AI in vertical farming stands as a captivating domain for exploration and innovation. Humanity is bestowed with an unprecedented opportunity to become researchers, practitioners, and visionaries, harnessing the promise of AI to transform agriculture, advocate for sustainable practices, and astonish the world with a future marked by abundance and ecological equilibrium. In essence, the era of AI in agriculture and vertical farming is a journey of boundless possibilities, limited only by our imagination and commitment to sustainability.

REFERENCES

[1] Zhang, L., Xu, Z., Xu, D., Ma, J., Chen, Y., & Fu, Z. (2020). Growth monitoring of greenhouse lettuce based on a convolutional neural network. Horticulture Research, 7(1).

[2] Hwang, Y., Lee, S., Kim, T., Baik, K., & Choi, Y. (2022). Crop Growth Monitoring System in Vertical Farms Based on Region-of-Interest Prediction. Agriculture, 12(5), 656.

[3] Gang, M.-S., Kim, H.-J., & Kim, D.-W. (2022). Estimation of Greenhouse Lettuce Growth Indices Based on a Two-Stage CNN Using RGB-D Images. Sensors, 22(15), 5499.

[4] Munirah Hayati Hamidon, & Ahamed, T. (2022). Detection of Tip-Burn Stress on Lettuce Grown in an Indoor Environment Using Deep Learning Algorithms. 22(19), 7251–7251.

[5] Osorio, K., Puerto, A., Pedraza, C., Jamaica, D., & Rodríguez, L. (2020). A Deep Learning Approach for Weed Detection in Lettuce Crops Using Multispectral Images. AgriEngineering, 2(3), 471–488.

[6] Hu, N., Wang, S., Wang, X., Cai, Y., Su, D., Purevdorj Nyamsuren, Qiao, Y., Yu, J., Bai, H., & Hang, W. (2022). LettuceMOT: A dataset of lettuce detection and tracking with re-identification of re-occurred plants for agricultural robots. 13.

[7] Lettuce NPK dataset. (n.d.). Nitrogen (N), Phosphorus (P), Potassium (K) Deficiencies in Lettuce. www.kaggle.com. Retrieved July 26, 2023.

[8] Lettuce Disease Computer Vision Dataset by PHS. (n.d.). Roboflow. Retrieved July 26, 2023.

[9] King Tide Farms Grows Hydroponic Produce for Top Restaurants in Charleston, SC. (n.d.). Freight Farms.

[10] M. H. Hamidon and T. Ahamed, “Detection of Tip-Burn Stress on Lettuce Grown in an Indoor Environment Using Deep Learning Algorithms,” Sensors, vol. 22, no. 19, p. 7251, Sep. 2022