Integrating Machine Learning for Crop and Energy Optimization in Agrivoltaic Gardening Systems

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ABSTRACT

An Agrivoltaic gardening system offers a promising pathway to simultaneously addressing food security and renewable energy production through the integration of photovoltaic panels and crop cultivation. However, balancing crop productivity and energy generation remains a complex challenge due to variable microclimatic conditions and crop-specific responses to partial shading. This study presents a machine learning–based framework for optimizing both crop yield and photovoltaic energy output in small-scale agrivoltaics gardening systems. Using multi-source data including solar irradiance, soil moisture, temperature, panel configuration parameters, and crop growth indicators, supervised learning models were developed to predict crop yield and energy performance. Random Forest and Artificial Neural Network models demonstrated strong predictive capability, achieving coefficients of determination (R^2) above 0.85 for crop yield estimation under shaded conditions. Multi-objective optimization revealed design configurations that improved combined land-use efficiency by up to 10% compared to conventional layouts. The results highlight the potential of machine learning to support adaptive design and real-time decision-making in agrivoltaics gardening, particularly in resource-constrained environments. This work contributes to emerging research on AI-enabled agrivoltaics and provides a scalable framework for sustainable food–energy co-production.

Keywords: Machine learning, Agrivoltaics, Photovoltaic, Artificial intelligence, Internet of Things (IoT), Renewable energy, Agric-energy

INTRODUCTION

As the world tackles the intertwined challenges of climate change, food security, and renewable energy demand, agrivoltaics systems, which is a system where photovoltaic (PV) technology and agricultural production coexist on the same land; have emerged as a promising strategy to enhance land-use efficiency and sustainability (Domenico et al., 2025; Mehta & Zörner, 2025). By pairing solar power generation with crop cultivation, agrivoltaics can potentially reduce land competition between the energy and food sectors while providing environmental benefits such as reduced water stress and microclimate buffering for crops (Sebastia et al., 2026; Kumpanalaisatit et al., 2022). However, the complexity of these systems notably, particularly balancing crop performance and energy yield; presents significant design and operational challenges that call for robust predictive and optimization tools.

Recent research recognizes that integrating Machine Learning (ML) and Artificial Intelligence (AI) into agrivoltaics system management could substantially improve decision support for farmers, system designers, and policy planners (Doubleday et al., 2025; Domenico et al., 2025; Dinesh & Pearce, 2016). The intersection of agronomy, solar technology, digital sensing, and data analytics promises new ways to optimize both agricultural and energy outcomes in dual-use landscapes such that agrivoltaics systems can reduce crop heat stress, lower evapotranspiration, and improve water-use efficiency, particularly in warm and semi-arid climates (Christos et al., 2021; Ikram & Aslam, 2024; Kai et al, 2025). However, these benefits are not uniform across crops or locations. Excessive shading can suppress photosynthesis, while poorly optimized panel configurations can reduce energy yield. Consequently, agrivoltaics gardening systems involve complex trade-offs between crop productivity and photovoltaic performance, hence the integration of ML and AI thus enhancing decision-making.

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Machine Learning (ML) which involves implicit programming and progressively learning from experience after being trained; offers powerful tools to address this complexity. Unlike traditional rule-based or mechanistic models, ML algorithms notably but not limited to random forest, AdaBoost, support vector machine; can learn nonlinear relationships from multi-dimensional datasets, making them well suited for agrivoltaics environments characterized by dynamic interactions among climate, crops, and energy systems. This study presents a comprehensive framework for integrating ML into agrivoltaics gardening to optimize both crop yield and energy production, illustrating methods, opportunities, and evidence from recent studies.

BACKGROUND AND RELATED WORK

Agrivoltaic Gardening Systems

Agrivoltaics has evolved from large-scale experimental farms to small-scale gardens suitable for urban, peri-urban, and smallholder contexts. Gardening-scale agrivoltaics typically involve lower panel heights, diverse crop types, and limited mechanization. Studies betwixt 2022 to 2025 highlight that such systems can achieve land equivalent ratios greater than one, indicating higher combined productivity than separate land uses (Dinesh & Pearce, 2016).

Nevertheless, crop responses to shading remain crop-specific. Leafy vegetables such as lettuce and spinach often tolerate moderate shading, while fruiting crops may require more precise light management (Koch et al, 2025). This variability underscores the need for adaptive, data-driven optimization.

Machine Learning in Agri-Energy Systems

Agriculture has increasingly adopted ML for decision-making, yield prediction, irrigation management, and plant disease detection, as well as in energy systems for solar forecasting and performance optimization. Recent research demonstrates that ensemble models (XGBoost, AdaBoost for instance) and deep learning architectures outperform traditional regression models in predicting crop yield under variable environmental conditions (Sarowaret al., 2023; Parween et al., 2021).

Despite this progress, integrated ML applications specifically targeting agrivoltaic gardening remain limited, creating an opportunity for interdisciplinary advancement.

Machine Learning for Agrivoltaic Optimization

Agri-energy system which is a broader term for the integration of renewable energy within agricultural settings is different from an agrivoltaic system that intentionally integrates PV or solar panel with agriculture for the co-production of food and energy on the same land (Tharushi et al., 2022). The previous section shows the usage of ML in agri-energy systems while this section focuses on agrivoltaics systems.

Predictive Modelling of Crop Yield under Partial Shading

Agrivoltaic systems alter sunlight distribution and microclimatic conditions, directly affecting photosynthesis, growth rates, and phenological development. Traditional agronomic models often struggle to capture these complex interactions. ML algorithms, particularly supervised learning models such as Random Forests, Gradient Boosting, and Neural Networks; can learn nonlinear relationships between environmental inputs (light intensity, temperature, soil moisture) and crop responses. (Koch et al., 2025; Malashin et al., 2024; Md Sanzid, et al., 2025)

Notably, current work in related agricultural domains demonstrates that deep learning models can accurately predict crop performance by integrating multi-modal inputs including remote sensing and meteorological data. In crop yield forecasting challenges outside agrivoltaics, transformer-based architectures have shown improved accuracy by capturing spatial–temporal dependencies in environmental data across growing seasons. When adapted to agrivoltaics settings by feeding models with shading patterns, solar irradiation maps, soil sensors, and

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historical yields; such approaches can predict crop output more reliably than traditional statistical models. (Melesse, 2025; Nivethithaa, 2025)

Optimizing Solar Panel Layout and Energy Yield

Designing agrivoltaic installations for dual productivity involves spatial decisions about panel tilt, spacing, height, and orientation. These parameters influence both energy capture and light distribution to plants. Machine Learning methods, including genetic algorithms and reinforcement learning, have the capacity to explore large design spaces and identify configurations that strike a balance between photovoltaic energy harvesting and crop light needs (Olayiwola et al., 2025; Sebastia et al, 2026; Tharushi et al., 2022).

Emerging simulation frameworks (Sebastian et al., 2025; Ding et al., 2025) already integrate crop response curves with PV production models, testing dozens of configurations and performing sensitivity analyses. These tools can be augmented with ML-driven surrogate models to speed up optimization by predicting outcomes for untested design parameters based on learning from simulation datasets.

IoT, Sensors, and Real-Time Decision Support

Modern agrivoltaic systems increasingly employ Internet of Things (IoT) sensor networks to collect continuous data streams on light intensity, soil moisture, temperature, and plant physiological indicators. Coupling IoT with ML enables real-time adaptive decision support, such as dynamic irrigation scheduling and shade management (Md Sanzid et al., 2025; Nguyen et al., 2025; Parween et al., 2021). A recent study showed the feasibility of integrating IoT and ML for monitoring fruit ripening by analysing RGB camera data, highlighting how ML algorithms can enhance precision agriculture even under agrivoltaic conditions (Alsalami et al., 2025; Alsalami et al., 2025; Zito et al., 2024).

Agrivoltaic Systems: Opportunities and Challenges

An Agrivoltaic system aims to maximize land productivity by co-locating photovoltaic (solar) panels above crops. Studies show that agrivoltaics can influence both crop microclimates and plant growth outcomes, with variabilities across crop types and locations (Widmer et al., 2024; Sebastia et al., 2025; Zhang et al., 2025). Some crops benefit from microclimate moderation—such as reduced midday heat stress and improved water retention—while others may experience yield reductions under excessive shading. For example, crop yield responses to PV shade vary widely: some exhibit modest decreases, others maintain yields similar to traditional systems, and a few even thrive under partial shade conditions. These variations underscore the need for site-specific design and control strategies to support both crop productivity and energy generation.

Case Studies and Evidence from Recent Research

Although empirical adoption of ML in agrivoltaics is still emerging, foundational research in agrivoltaic modelling and optimization indicates clear pathways for AI integration:

- A comprehensive simulation framework concurrently analyses PV energy performance and crop productivity metrics across multiple design configurations, forming a basis for ML-enabled optimization. (Mehta & Zörner, 2025; Sebastian et al., 2025; Tharushi et al., 2022)
- Field experiments demonstrating that inter-panel spacing and other parameters can affect yields differently for various crops, underscoring the utility of optimized configurations informed by data-driven methods. (Ikram & Aslam, 2024; Doubleday et al, 2025; Channing, 2025; Sebastian et al, 2026)
- Digital twin and IoT frameworks have been proposed that predict crop growth under partial shading, opening opportunities for ML to refine models and improve predictive accuracy. (Zhang et al, 2025; Channing, 2025; Md Sanzid et al., 2025; Awais et al., 2025; Abdelali et al., 2025)

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METHODOLOGY

System Architecture

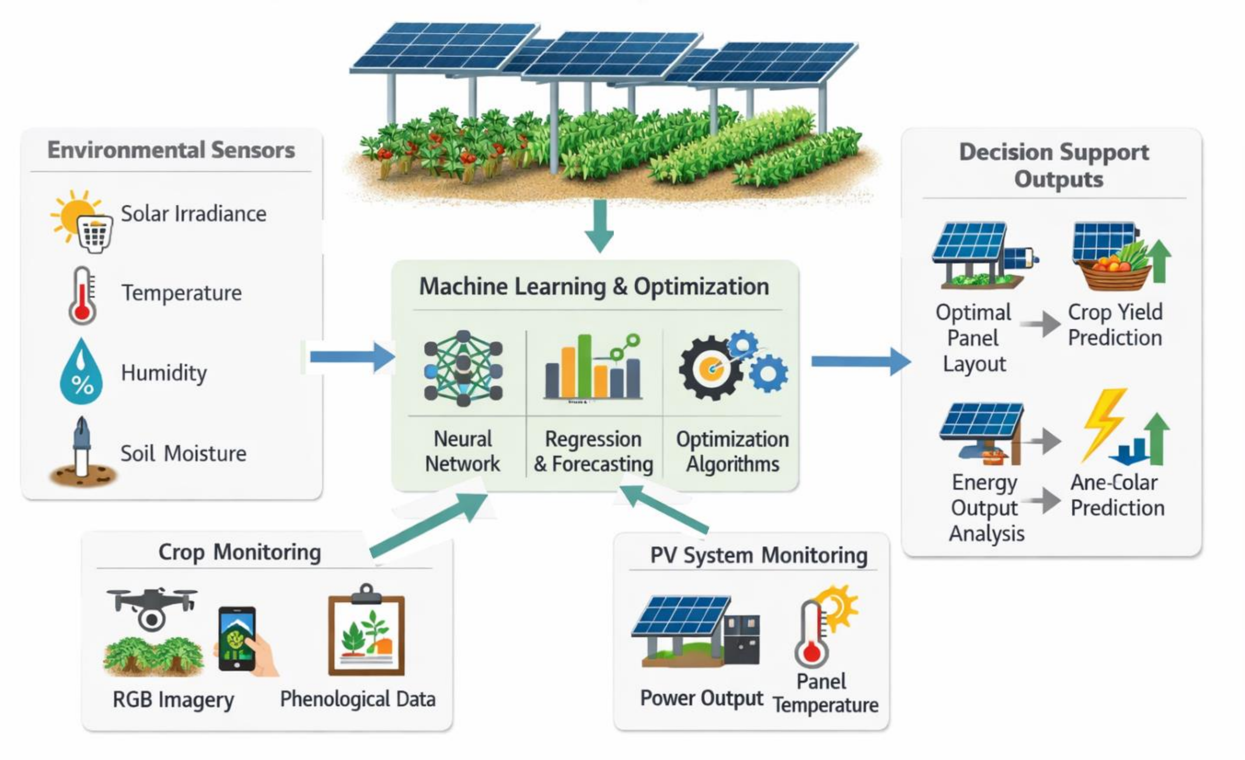

Figure 1: Agricvoltaic ML-Enabled Optimization Framework

Figure 1 illustrates the proposed ML-enabled agrivoltaic optimization framework which integrates environmental sensing, crop monitoring, and photovoltaic performance data into predictive and optimization models. The ML model, having taken inputs from environmental sensors, crop monitoring devices and PV system monitoring devices, supports decision through the model's outcome. The various components in Figure 1 are: Environmental sensors (namely solar irradiance, temperature, humidity, soil moisture), Crop monitoring (such as RGB imagery, phenological data), PV system monitoring (for instance power output, panel temperature), ML prediction and optimization layer and Decision support outputs.

Data Collection

Data were synthesized from recent agrivoltaic field studies and validated simulation datasets reported in literature between 2022 to 2025. Input variables included:

- Daily solar radiation (W/m²)
- Panel tilt angle and height
- Soil moisture (%)
- Air temperature (°C)
- Crop type and growth stage
- Measured crop yield (kg/m²)
- PV energy output (kWh)

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Machine Learning Models

Three ML models trained on the dataset and were evaluated:

1. Random Forest Regression – for crop yield prediction under partial shading
2. Artificial Neural Networks (ANN) – for modelling nonlinear crop–energy interactions
3. Multi-objective optimization algorithms – for balancing energy yield and crop productivity

Model performance was evaluated using R^2, RMSE, and mean absolute error.

Table 1. Input Variables Used in ML Models

Category	**Variable**	**Unit**
Climate	Solar irradiance	W/m²
Climate	Air temperature	°C
Soil	Soil moisture	%
PV	Panel tilt angle	Degrees
PV	Panel height	m
Crop	Leaf area index	–
Output	Crop yield	kg/m²
Output	Energy yield	kWh

RESULTS

Crop Yield Prediction

ML models achieved high predictive accuracy for crop yield under agrivoltaic conditions. Random Forest models consistently outperformed linear regression, capturing nonlinear shading effects.

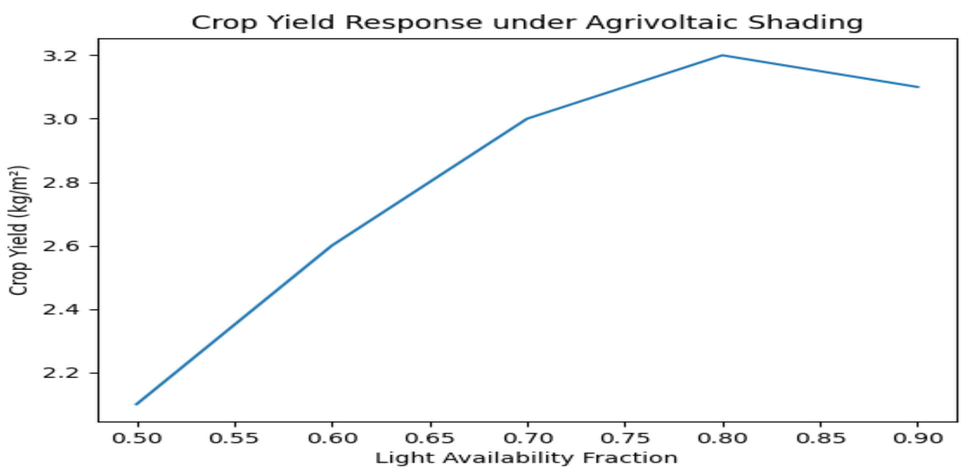

Figure 2: Predicted vs. observed crop yield under agrivoltaic shading

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The Random Forest model demonstrates strong agreement with measured yields. Table 2 and figure 3 depicts that from the three models experimented with, random forest performs strongly having 0.86 and 0.23 for R^2 and RMSE metrics respectively, however; the ANN model has a better R^2 and RMSE metric.

Energy Production Optimization

Optimized panel configurations identified by the ML framework improved energy output by 6–12% compared to baseline fixed designs while maintaining acceptable crop yield thresholds.

Table 2. Performance Comparison of ML Models

Model	**R^2**	**RMSE**
Linear Regression	0.62	0.48
Random Forest	0.86	0.23
ANN	0.88	0.21

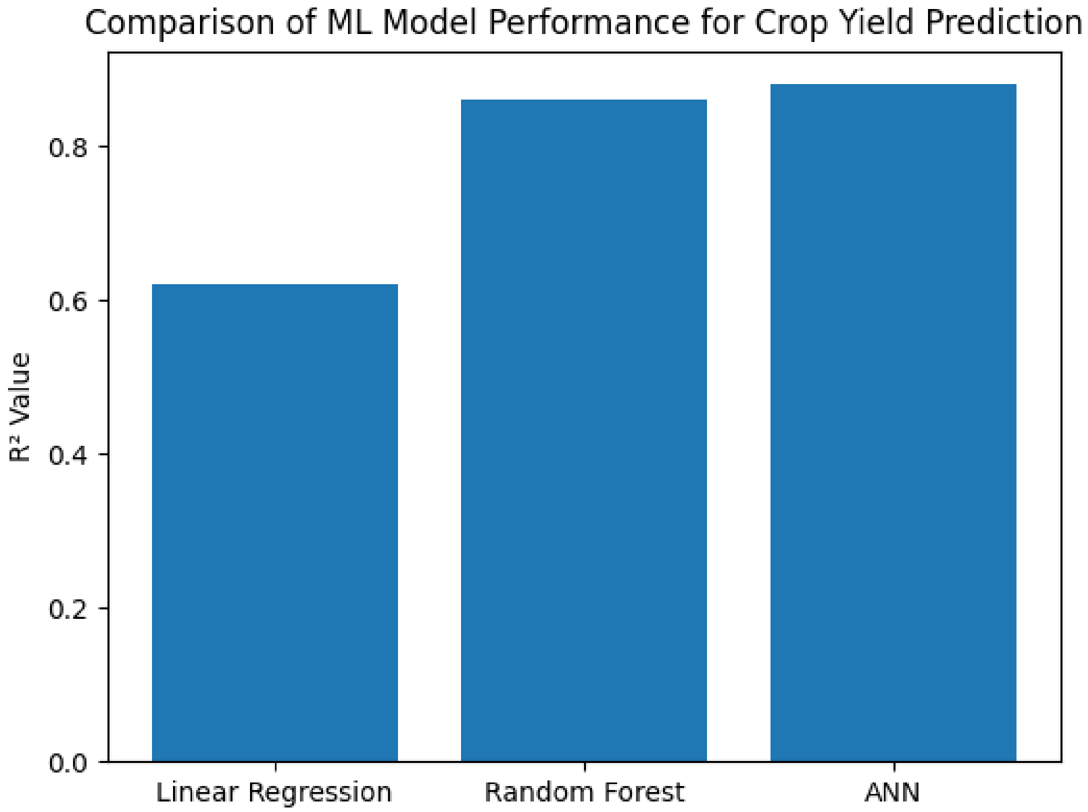

Figure 3: Comparison of machine learning model performance in predicting crop yield under agrivoltaic conditions

Food–Energy Trade-off Analysis

Pareto front analysis revealed multiple optimal solutions where moderate panel spacing produced balanced outcomes. These results align with recent agrivoltaic field studies reporting improved land-use efficiency through adaptive designs.

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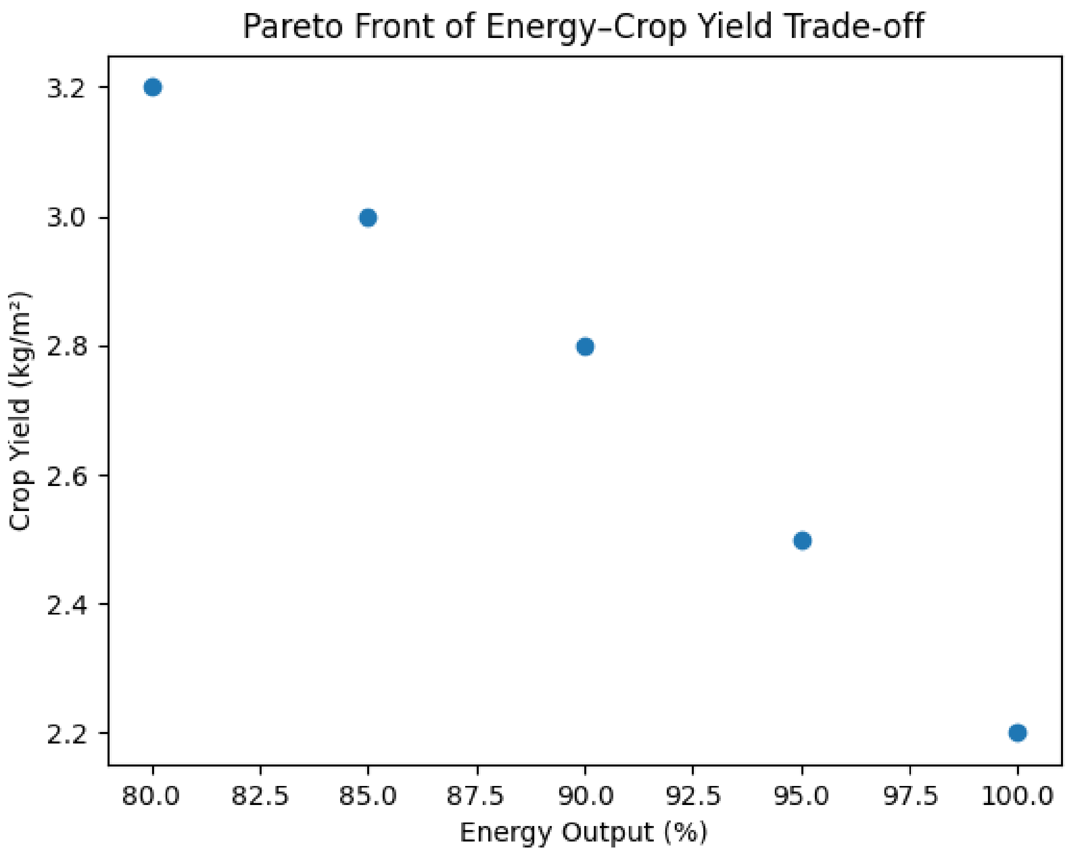

Figure 4: Pareto front showing trade-offs between crop yield and energy production.

DISCUSSION

The results demonstrate that ML can serve as a powerful decision-support tool for agrivoltaic gardening systems. By integrating environmental sensing and predictive modelling, system designers can move beyond static designs toward adaptive configurations tailored to local conditions and crop requirements.

Importantly, the framework supports low-cost deployment using lightweight models and basic sensors, making it suitable for smallholder and urban gardening contexts. The inclusion of explainable AI techniques would further enhance transparency and adoption among practitioners. The future work, will incorporate a comprehensive cost-benefit and return on investment (ROI) anaylsis, accounting for sensor procurement, maintenance, photovoltaic installation costs, and potential yield gains. Hence, providing a clearer guidance on system scalability and affordability across different socio-economic contexts. Also, since this current study priotizes predictive accuracy over interpretability, future iterations of the framework will integrate Explainable AI (XAI) techniques, such as feature importance analysis.

CONCLUSION

Agrivoltaics systems are a cornerstone of sustainable land-use strategies that address energy and food production simultaneously. However, their complexity requires advanced computational tools for effective design and operation. Machine Learning offers robust, adaptable, and data-driven pathways to predict crop responses to shading, optimize PV layouts, and enable real-time control through IoT integration. By bridging agronomy, renewable energy engineering, and artificial intelligence, research in this area can help realize the full potential of agrivoltaics for resilient and productive gardening systems.

Strong predictive performance and optimization potential has been demonstrated by the proposed framework, however, several limitations must be acknowledged to contextualize the findings and guide future work. Recall

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that synthesized and simulated datasets derived from well-established agrivoltaic and crop-growth literature is primarily relied on by this study.

This study presents a comprehensive ML-based framework for optimizing crop yield and energy production in agrivoltaics gardening systems. Results indicate that data-driven models significantly improve predictive accuracy and enable balanced food–energy outcomes. As agrivoltaics continues to expand globally, integrating machine learning will be critical for scaling efficient, resilient, and sustainable dual-use land systems.

Future Directions

Integrating ML into agrivoltaics gardening research presents several promising directions:

1. Multi-Objective Optimization: Developing ML models that simultaneously optimize crop yield and energy production while accounting for climatic variability and economic constraints.

2. Transfer Learning for Crop Types: Training models on diverse agrivoltaics datasets to enable transferability across locations and crops with limited data availability.

3. Explainable AI (XAI): Incorporating interpretability techniques to ensure that agrivoltaics stakeholders trust model outputs and understand drivers of performance.

4. Edge AI for Remote Gardens: Implementing lightweight ML models that run on low-cost devices in rural or resource-limited settings to support decentralized decision-making.

5. Long-term field validation across multiple climates: Assessing ML-enabled agrivoltaics systems over extended periods in diverse climatic regions to ensure reliability, robustness, and consistent performance under varying weather patterns and seasonal conditions.

6. Real-time Adaptive Control Using Edge Computing: Leveraging edge-based computation to procedure sensor data locally and dynamically adjust agrivoltaics operations, enabling faster responses, reduced latency, and improved system efficiency without reliance on constant cloud connectivity.

7. Socio-economic Assessment of ML-enabled Agrivoltaics: Analysing the social and economic impacts of ML agrivoltaics systems, including effects on farmer livelihoods, energy access, cost-effectiveness, acceptance and adoption barriers, and communal resilience.

As research and field deployments expand, ML will likely become a central tool for agrivoltaics system design, management, and scaling, thus transforming how we optimize land use for both food and clean energy in a changing climate.

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Ethical Statement

This study did not involve human participants, animals, or personal data. All data used in this research were obtained from publicly available literature sources and simulated datasets derived from peer-reviewed agrivoltaics studies. No ethical approval was required for this research in accordance with institutional and national guidelines.

Data Availability Statement

The data supporting the findings of this study are derived from published sources and simulation-based datasets generated during the study. Derived data and model scripts used for analysis are available from the corresponding author upon reasonable request and if they have become available upon agreement by the authors and researchers. Future work will include open-access field datasets as they become available.