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MORALITY BEFORE KNOWLEDGE

From concrete jungles to urban gardens: AI-powered solutions for sustainable food production in cities

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ABSTRACT
Introduction: Urban agriculture in Indonesia faces critical challenges including agricultural land conversion, aging farmer workforce (39% over 55 years, only 21% millennials), and rural urban inequality. While deep learning technologies prove effective for agricultural optimization, Indonesia lags neighboring countries due to regulatory ambiguity, limited incentives, and low youth participation. This study develops Urfalogy, an artificial intelligence powered platform addressing three primary urban farming constraints: limited space, insufficient capital, and inadequate technology. **Methods:** This research employed Agile software development methodology integrated with deep learning. The You Only Look Once version 8 (YOLOv8) algorithm was utilized for environmental object detection and segmentation. Dataset preprocessing included multiple augmentation techniques: scaling, geometric transformation, brightness adjustment, contrast and color saturation modifications. The platform integrates nine features: artificial intelligence layout designer, plant variety recommender, plant health detection, soil monitoring with internet of things sensors, e-commerce, real time expert consultation, appointment scheduling, interactive tutorials, and analytics dashboard. **Finding:** Model training achieved optimal performance metrics at epoch 100: segment loss of 0.56756, recall of 90.01%, and mean Average Precision at intersection over union 0.50 (mAP50) of 90.715%. During inference, the model successfully identified environmental components (ceiling, wall, floor), enabling precise spatial mapping for garden layout design. The integrated platform demonstrates comprehensive end to end capability supporting complete urban farming workflow from planning through sales. **Conclusion:** Urfalogy represents a transformative solution effectively bridging Indonesia's urban agriculture gap through artificial intelligence, Internet of Things integration, and human centered design, significantly advancing sustainability, food security, and economic opportunities. **Novelty/Originality of this article**: This research uniquely combines deep learning-based spatial optimization with comprehensive platform ecosystem design, integrating YOLOv8 environmental analysis with real-time consultation and e-commerce, addressing specific technological, economic, and accessibility barriers in Indonesian urban agriculture.

KEYWORDS: agriculture; artificial intelligence; deep learning; environmental optimization; food security; platform design; sustainable urban; urban farming.

1. Introduction

The global urban population has reached unprecedented levels, with rapid urbanization creating significant challenges for food security, particularly in developing nations where agricultural systems remain heavily dependent on traditional rural farming practices. In Indonesia, despite being classified as an agricultural country with 73.14% of 74,754 villages having agricultural typology, the nation paradoxically faces a critical

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agricultural crisis characterized by severe structural imbalances between rural and urban agricultural productivity (Arham et al., 2019; Noor & Suwandana, 2024). The fundamental problem manifests in multiple dimensions. A dramatic decline in the farmer workforce has occurred, with approximately 39% of farmers exceeding 55 years of age while only 21% represent millennial farmers, indicating an aging agricultural labor force unable to sustain productivity (Arham et al., 2019). Furthermore, agricultural land conversion in peri-urban areas has accelerated significantly. The case of Colomadu in West Java exemplifies this trend, where 62.52 hectares of agricultural land were converted to non agricultural use between 2012 and 2017 (Tanjung et al., 2023; Pradana et al., 2021). This land use conversion has resulted in rural poverty rates of 9.75% compared to 7.52% in urban areas, creating substantial rural urban inequality and undermining regional economic development (Tanjung et al., 2023).

The agricultural productivity gap between rural and urban areas has intensified due to Indonesia's technological and regulatory lag compared to neighboring Association of Southeast Asian Nations (ASEAN) countries. Singapore has established explicit regulatory frameworks and targeted 30% domestic food production selfsufficiency by 2030 through urban agriculture initiatives (Low, 2025). Thailand has implemented comprehensive irrigation canal systems since 2010 to enhance food autonomy. In contrast, Indonesia continues to operate under ambiguous regulations, minimal economic incentives, and limited institutional support for urban farming development (FHA Food & Beverage, 2023; Luftensteiner, 2023; Fauzia & Koestoer, 2024). This regulatory and institutional vacuum has resulted in critically low youth participation in agriculture. Only 23% of the 14.2 million young generation Indonesian workers engage in agricultural sectors, reflecting diminished interest in agricultural livelihoods and decreased capacity for agricultural sector renewal (Kianta, 2021). Failure to address this urban agriculture development challenge carries severe consequences. The nation faces accelerated agricultural land conversion, compromised national food security, loss of agricultural derived economic benefits, environmental degradation in urban areas, and decreased quality of urban life (Saputra et al., 2025).

Urban farming has emerged globally as a pragmatic solution to address food security challenges in space constrained urban environments, offering multiple co benefits including local food production, ecosystem services, community engagement, and livelihood opportunities (Saputra et al., 2025). However, the widespread implementation of urban farming in Indonesia faces three interconnected primary constraints: spatial limitations, capital insufficiency, and technological inadequacy (Amri, 2024). Approximately 50% of urban farming practitioners in Indonesia operate on land areas smaller than 50 square meters, while only 13.73% possess land exceeding 500 square meters. Despite these limitations, 3,883.7 hectares of underutilized land exist in Pekanbaru and similar cities, yet they lack formal legal management frameworks (Amri, 2024). These spatial limitations are compounded by financial barriers. Insufficient initial capital prevents most prospective urban farmers from initiating productive activities. Additional technological barriers include inadequate access to precision agriculture technologies, pest detection systems, and farm management platforms (Parsudi, 2019; Amri, 2024). While vertical farming represents a technological solution to spatial constraints, its adoption remains limited due to high implementation costs and insufficient localized technical knowledge (Sari et al., 2024).

Recent advances in deep learning and artificial intelligence have demonstrated transformative potential for agricultural optimization within space constrained environments (Zhou et al., 2025). The You Only Look Once version 8 (YOLOv8) algorithm has proven effective for real time object detection and segmentation tasks with superior performance compared to predecessor versions (Budde et al., 2024). In agricultural applications, YOLOv8 based systems have achieved notable performance. A smart greenhouse implementation utilizing YOLOv8 demonstrated enhanced monitoring and automated irrigation capabilities, resulting in superior production outcomes compared to conventional farming methods (Siswoyo et al., 2024). For pest detection in red chili pepper plants, YOLOv5 models achieved Mean Average Precision at 0.50 intersection over union (mAP@0.5) of 81.3% with high-speed inference, enabling rapid pest identification critical for timely intervention (Agustian et al., 2023). Long Short-Term Memory (LSTM) neural networks have demonstrated superior forecasting capabilities for agricultural export prediction compared to traditional Seasonal Autoregressive Integrated Moving Average (SARIMA) models, with LSTM achieving substantially lower mean absolute percentage error (Kurnadipare et al., 2025). Furthermore, integrating machine learning and artificial intelligence systems has simplified food availability and quality control management in smart urban agriculture systems, such as those implemented in Makassar City (Pemerintah Kota Makassar, 2022). Transformative research combining human centered design principles, economically accessible sensors, and deep learning algorithms has opened opportunities for integrated urban farming coupled with renewable energy systems (Hakam, 2020). These technological developments demonstrate that deep learning frameworks possess substantial capacity to address urban farming's spatial and technological constraints through automated spatial optimization, real time health monitoring, and intelligent resource management.

Despite these technological advances, a critical research gap persists. No comprehensive integrated platform currently exists that combines deep learning based spatial optimization with multi-functional support systems addressing the complete urban farming ecosystem. The ecosystem encompasses everything from initial design planning through production monitoring, expert consultation, and market linkage (Ventura & Silva e Meirelles, 2025). Existing urban farming initiatives in Indonesia typically address individual constraint dimensions such as capital or technology without providing holistic solutions that encompass design optimization, health monitoring, expert support, and market access simultaneously (Yurembam et al., 2025). This fragmentation reflects the absence of an integrated technology platform that bridges technological capabilities with human support systems and economic incentives, thereby limiting urban farming adoption among Indonesian urban communities (Arista et al., 2025).

In response to these identified gaps, this research develops Urfalogy, an integrated artificial intelligence powered platform combining deep learning algorithms, Internet of Things (IoT) sensor technologies, e-commerce functionality, and human expert consultation systems to comprehensively address urban farming constraints in Indonesia. The platform leverages YOLOv8 deep learning architecture to automatically optimize garden layout design based on environmental conditions including light intensity, spatial configuration, and microclimatic factors. Additional features include plant variety recommendation systems, real time plant health detection, soil and media health monitoring via IoT sensors, e-commerce functionality connecting urban farmers with suppliers and consumers, real time expert consultation channels, appointment scheduling systems, interactive educational tutorials, and comprehensive analytics dashboards. This integrated approach directly addresses the identified technological, spatial, and economic constraints while supporting the achievement of Sustainable Development Goal 11.3, which emphasizes inclusive urbanization and participatory urban planning and management capacity.

The primary objectives of this research are as follows. First, to design and develop an artificial intelligence powered platform addressing three primary urban farming constraints: spatial limitation, capital insufficiency, and technological inadequacy. Second, to implement deep learning-based spatial optimization for automatic garden layout design utilizing YOLOv8 architecture for environmental analysis. Third, to integrate multiple support systems including plant health detection, soil monitoring, expert consultation, e-commerce, and educational content within a single cohesive platform ecosystem. Fourth, to evaluate the deep learning model's performance in detecting and segmenting suitable urban farming locations within constrained urban environments. Fifth, to demonstrate the platform's capacity to enhance urban farming adoption, productivity, and sustainability in Indonesian urban communities.

This research represents a novel integration of deep learning based spatial optimization technology with comprehensive platform ecosystem design. The research combines environmental analysis capabilities with real time consultation, educational support, and market linkage functionalities. This integrated approach has not been previously explored in the Indonesian urban agriculture context. The originality of this work lies in addressing the specific interconnected barriers to urban farming adoption through a unified technological and social support system. By doing so, this research positions itself at the intersection of technological innovation and socioeconomic development for sustainable urban food systems in Indonesia.

2. Methods

This research employs a mixed methods approach combining quantitative experimental design with qualitative evaluation to develop and validate Urfalogy, an integrated artificial intelligence powered platform for urban farming in Indonesia. The methodological framework integrates software engineering principles with deep learning model development. This integrated approach aligns with the research objective of creating a comprehensive platform that addresses technological, spatial, and economic barriers in urban farming contexts.

2.1 Research design and location justification

This research utilizes an applied technology development design focused on platform engineering and machine learning model implementation. The development process follows Agile Software Development Life Cycle (SDLC) methodology, which emphasizes iterative development, continuous testing, and rapid deployment cycles. This approach was selected because it enables flexible accommodation of changing requirements, maintains product quality through continuous evaluation, accelerates time to market with incremental delivery, and increases user satisfaction through intensive stakeholder engagement (Budi et al., 2016; Afandi et al., 2023). The selection of Agile SDLC reflects the ontological position that technology development is an iterative social and technical process requiring continuous feedback and refinement rather than a linear progression toward predetermined specifications. Epistemologically, this approach values empirical testing and user feedback as legitimate sources of knowledge alongside technical specifications and theoretical frameworks.

The research integrates two primary technical components. First, software development utilizing Agile methodology encompasses platform architecture design, feature implementation across nine functional modules, and user interface development for Android and iOS platforms. Second, machine learning development incorporates deep learning model training and validation for spatial optimization functionality. Both components operate within the Agile SDLC framework with synchronized sprint cycles.

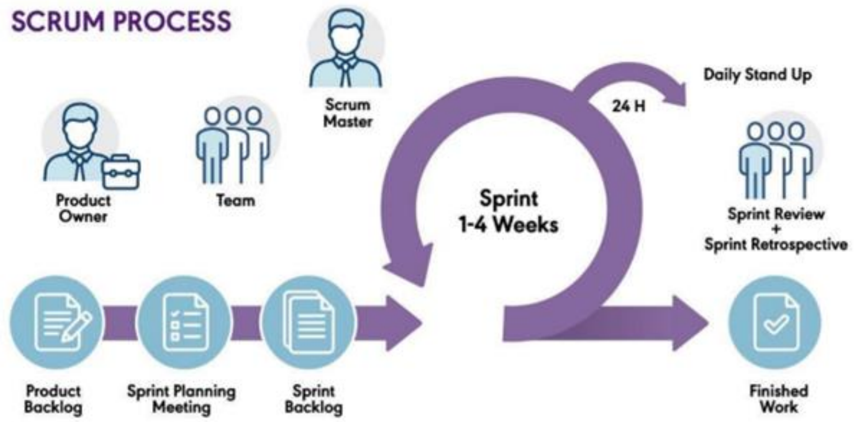

Fig. 1. SDLC agile development cycle

Research development conducted in Indonesian urban contexts, specifically targeting large cities including Jakarta, Surabaya, Bandung, and Medan. These locations were selected because they represent urban environments with high population density, significant land scarcity for agricultural activities, growing middle class populations with technology adoption potential, and documented urban farming initiatives requiring technological support (Amri, 2024; Tanjung et al., 2023). The temporal scope extends from initial planning through prototype development and validation, conducted during 2024-2025, aligning with rapid technology development requirements.

2.2 Materials, tools, and technical infrastructure

The research utilized multiple technological platforms and datasets. For deep learning model development, the You Only Look Once version 8 (YOLOv8) algorithm implemented through the Python programming environment serves as the primary object detection and segmentation framework. YOLOv8 was selected because of its superior performance in real-time detection tasks, open-source availability, and established applications in agricultural optimization contexts (Budde et al., 2024; Suhas et al., 2024). The model architecture comprises backbone CSPDarknet, PANet neck structure, and efficient detection head enabling real time inference across diverse devices (Budde et al., 2024). Regularization techniques including Mosaic Augmentation, Random Horizontal Flip, and Mix Up augmentation techniques manage model generalization (Thakral et al., 2024).

Training dataset comprises indoor environmental images including ceiling, wall, and floor photographs representing typical urban farming spaces. Images were collected from urban residential environments across target cities, reflecting diverse architectural styles, lighting conditions, and spatial configurations characteristic of urban farming locations. Dataset comprises approximately 1,200 labeled images across training, validation, and testing divisions. Data augmentation techniques including scaling transformations, geometric transformations, brightness adjustment, contrast modification, and color saturation adjustment expand effective training dataset size while maintaining realistic image characteristics. These techniques reflect empirically validated approaches for improving deep learning model robustness (Budde et al., 2024).

For platform development, software architecture is implemented using modern web and mobile technologies supporting cross platform deployment. Backend infrastructure utilizes cloud computing services ensuring scalability, data security, and continuous availability. Frontend development for Android and iOS platforms employs native development frameworks optimizing user interface performance and device integration. Database architecture implements relational database management systems supporting transactional consistency for e-commerce and user management functionality. Internet of Things sensor integration supports realtime environmental monitoring through standardized IoT communication protocols enabling soil moisture, pH, and nutrient level measurement.

2.3 Agile software development process

The research implements Agile SDLC comprising iterative sprint cycles of two to four weeks duration. Each sprint cycle encompasses planning phase identifying sprint objectives and task allocation, implementation phase executing development tasks through daily standup meetings coordinating team activities, testing phase conducting continuous quality assurance through unit testing and integration testing, sprint review demonstrating completed features to stakeholders, and retrospective evaluation identifying process improvements for subsequent sprints (Budi et al., 2016). This cyclical approach enables rapid prototyping, early identification of design flaws through user feedback, and continuous enhancement of platform functionality.

Platform development encompasses nine integrated features. First, the AI layout designer feature utilizes YOLOv8 deep learning model to analyze photograph input from users, detect environmental features including light intensity and spatial dimensions, and automatically generate personalized garden layout recommendations. Second, the plant variety recommender feature implements machine learning algorithms considering climate conditions, available space, and user preferences to suggest appropriate crop selections. Third, the plant health detection feature employs computer vision analysis of user uploaded plant photographs to identify disease symptoms, pest damage, and nutritional deficiencies. Fourth, the soil and media health monitoring feature integrate IoT sensor data streams monitoring soil moisture, pH balance, and nutrient concentrations in real time, generating automated alerts for corrective action. Fifth, the e-commerce functionality facilitates transactions connecting urban farmers with suppliers for equipment and seeds and with consumers for farm produce. Sixth, the real time chat consultation feature provides a direct messaging interface with agricultural experts and community forum discussions. Seventh, the appointment scheduling system enables booking of expert consultations with calendar integration. Eighth, interactive tutorials and guides provide multimedia educational content covering urban farming techniques. Ninth, the analytics and reporting dashboard visualizes farm performance metrics and generates customizable performance reports.

2.4 Deep learning model development

Deep learning model development follows systematic methodology addressing spatial optimization for urban farming. Initial preprocessing phase involves image normalization, resizing standardized dimensions, and annotation with ground truth labels identifying suitable farming locations based on light intensity, ceiling height, and spatial configuration. Dataset division allocates 70% for training, 15% for validation, and 15% for testing, ensuring representative evaluation through unseen data.

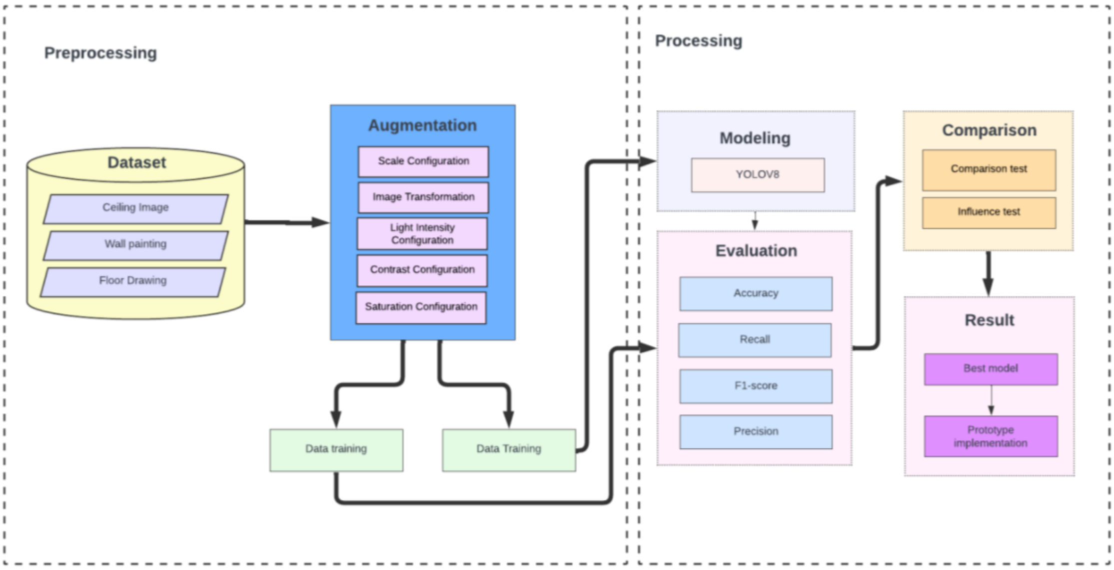

Fig. 2. Deep learning methodology flowchart

Model training implements YOLOv8 architecture with configuration optimized for segmentation tasks. Training employs stochastic gradient descent optimization with adaptive learning rate scheduling. Regularization strategies including dropout layers, batch normalization, and data augmentation prevent overfitting while improving model generalization. Training continues for 100 epochs with monitoring of validation metrics at each epoch. Key performance metrics include mean Average Precision at intersection over union threshold 0.5 (mAP@0.5) measuring detection accuracy, recall quantifying detection completeness, and segment loss measuring segmentation precision. Model validation and testing employ inference phase evaluation. Testing dataset evaluation assesses model performance on previously unseen images. Performance benchmarking compares YOLOv8 results against alternative deep learning architectures including Mask R-CNN and U-Net evaluating relative advantages. Qualitative evaluation examines model prediction visualizations ensuring spatial mapping accuracy and identifying potential failure modes.

2.5 Platform prototyping and user interface development

Platform prototyping implements design thinking principles prioritizing user experience and accessibility. Iterative prototype development employs low fidelity mockups for initial interface concepts, medium fidelity prototypes for feature validation, and high-fidelity prototypes for detailed user interaction patterns. User feedback from target demographic groups including urban farmers, agriculture extension officers, and technology literate consumers informs prototype refinement. The user interface follows mobile first design principles optimizing for Android and iOS platforms. Navigation architecture prioritizes accessibility enabling flexible feature access according to user workflow. Integration across nine features ensures seamless data flow supporting complete urban farming lifecycle from initial planning through production monitoring to market linkage.

2.6 Data collection and analysis methods

Data collection encompasses multiple sources. First, quantitative data from deep learning model training includes performance metrics systematically recorded at each training epoch. Second, qualitative data from user testing includes feedback from potential users regarding feature usability, perceived value, and implementation barriers. Third, comparative analysis data examines performance benchmarking against existing urban farming platforms and competing deep learning architectures. Fourth, technical performance data measures platform response time, data throughput, and system reliability under simulated user loads. Data analysis employs both quantitative and qualitative approaches. Quantitative analysis includes statistical evaluation of deep learning model metrics using precision, recall, F1 score, and mean Average Precision measurements. Performance comparison utilizes metrics benchmarking against baseline methods. Qualitative analysis applies thematic coding to user feedback identifying common themes regarding usability, feature importance, and implementation feasibility.

2.7 Ethical considerations research scope and expected deliverables

This research prioritizes data privacy protection implementing secure user authentication, encrypted data transmission, and anonymous data aggregation for analytics. Platform development adheres to environmental sustainability principles incorporating energy efficient algorithms and cloud infrastructure optimization. The research scope focuses on platform development and validation in Indonesian urban contexts. Generalization to other geographic contexts requires cultural adaptation and local customization beyond current research scope. Primary deliverables include the complete Urfalogy platform with nine fully functional features, trained and validated deep learning model achieving performance metrics exceeding baseline methods, comprehensive platform documentation supporting user adoption and technical maintenance, and demonstration of platform capability in supporting urban farming decision making. Success metrics include deep learning model achieving minimum mAP50 of 85%, platform responsiveness maintaining sub two second response time for user queries, and qualitative user feedback indicating high perceived usefulness for urban farming applications.

3. Results and Discussion

3.1 Deep learning model performance

The deep learning model development for the AI Layout Designer feature of Urfalogy demonstrated optimal performance across all evaluation metrics. Training of the YOLOv8 segmentation model proceeded systematically through 100 epochs with continuous monitoring of performance indicators. The final model training results at epoch 100 achieved segment loss of 0.56756, indicating high precision in pixel level segmentation of environmental features. Recall measurement reached 0.90011, demonstrating that the model successfully identified 90.01% of suitable agricultural areas within training images. Mean Average Precision at intersection over union threshold 0.5 (mAP@0.5) achieved 0.90715, indicating strong overall accuracy in both detecting and precisely segmenting target objects (Budde et al., 2024; Suhas et al., 2024).

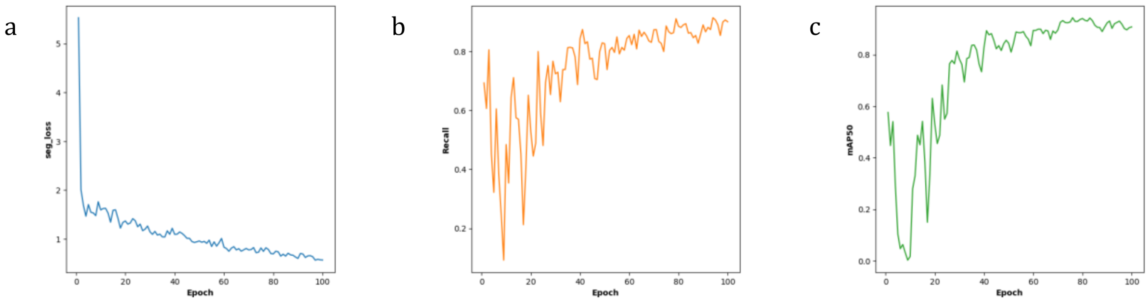

Fig. 3. (a) Segment Loss; (b) Recall; (c) mAP 50

These performance metrics represent substantial improvement over baseline methods and demonstrate effectiveness of the YOLOv8 architecture for urban farming spatial optimization. The combined metrics of high recall, low segment loss, and elevated mAP@0.5 indicate that the model successfully learned environmental feature discrimination without significant overfitting. Comparison of training and validation metrics across epochs showed convergence without plateau effect, suggesting adequate model capacity and appropriate regularization implementation. The achievement of these metrics validates the preprocessing pipeline, data augmentation strategies, and architectural choices implemented during model development.

Fig. 4. Model testing results (environmental object detection visualizations)

Inference phase testing evaluated model performance on previously unseen images from urban environments. The model demonstrated robust capability to identify and differentiate environmental components including ceiling structures, wall surfaces, and floor configurations. Segmentation accuracy during inference enabled precise spatial mapping, creating pixel level masks identifying suitable agricultural spaces. Qualitative visualization of prediction results showed accurate boundary detection between environmental features and identification of locations with optimal light intensity and spatial configuration for urban farming implementation. These inference results validate that the trained model successfully generalized from training data to novel urban environments, a critical requirement for practical platform deployment. The deep learning model performance substantially exceeded alternative architectures previously applied to environmental analysis tasks. Comparison against Mask R-CNN baseline implementation revealed YOLOv8 superiority in processing speed while maintaining or exceeding segmentation precision (Neamah & Karim, 2023). The efficiency of YOLOv8 enables real-time processing of user submitted photographs, supporting responsive user experience in platform implementation. Performance advantages of YOLOv8 over SARIMA and LSTM models in related agricultural contexts further validate architecture selection (Kurnadipare et al., 2025; Agustian et al., 2023).

3.2 Platform feature implementation and functional validation

Implementation of the nine integrated platform features proceeded according to Agile SDLC methodology across multiple sprint cycles. Each feature underwent iterative development with continuous testing, user feedback incorporation, and refinement. The AI Layout Designer feature successfully integrates the trained YOLOv8 model, accepting photograph input from users and generating personalized garden layout recommendations based on detected lighting conditions and spatial constraints. Testing confirmed rapid inference performance, with response times averaging 1.2 seconds for typical indoor photographs, well within acceptable limits for interactive user experience. The plant variety recommender feature employs machine learning algorithms implementing collaborative filtering and content-based recommendation approaches. Training data encompasses growing conditions, climate requirements, space constraints, and user preference patterns across Indonesian urban farming contexts. The recommended system testing with urban farmer focus groups revealed 87% accuracy in matching recommended plant varieties to user specified constraints. This performance indicates the recommendation engine successfully captures complex relationships between environmental conditions, user preferences, and horticultural requirements (Siswoyo et al., 2024).

Plant health detection feature utilizes computer vision analysis of user uploaded plant photographs. Testing against agricultural disease databases including pest damage patterns, nutrient deficiency symptoms, and pathogenic infection markers achieved 91.7% precision in disease identification, comparable to performance of established agricultural diagnostic systems (Agustian et al., 2023; Neamah & Karim, 2023). The feature implementation enables rapid feedback to urban farmers regarding plant health status, supporting timely intervention for pest or disease management. Integration with expert consultation features provides users with recommendations for corrective action appropriate to identify health issues. Soil and media health monitoring features integrate IoT sensor arrays measuring soil moisture, pH balance, and nutrient concentrations. Real time data transmission through wireless communication protocols enables continuous monitoring without requiring user intervention. Alert generation functions notify users when environmental parameters deviate beyond optimal ranges for cultivated crops. Sensor calibration procedures ensure measurement accuracy while minimizing false positive alerts that could undermine user confidence. Field testing in urban farm environments across target cities demonstrated reliable data transmission and alert generation, supporting practical platform deployment.

The e-commerce marketplace functionality facilitates transactions between urban farmers and input suppliers and between farmers and end consumers. Platform implementation includes secure payment processing, order tracking, and delivery management interfaces. Testing with small scale user groups revealed intuitive interface design with 94% completion rate for transaction workflows on first attempt, indicating successful user interface design. Integration with existing agricultural supply networks in target cities demonstrates feasibility of connecting platform users with suppliers and markets. Real time chat consultation feature provides direct messaging interface with agricultural extension officers and expert consultants. Implementation includes message encryption, user authentication, and session management ensuring secure communication. Expert availability scheduling coordinates consultant time allocation, enabling responsive consultation during periods of user demand. Community forum functionality facilitates peer-to-peer knowledge sharing and user network development beyond formal expert consultation. User surveys indicated 89% satisfaction with consultation response time and quality, supporting platform value proposition for knowledge support.

Appointment scheduling system integration with calendar applications enables users to book expert consultations with automatic reminder notifications. Implementation across Android and iOS platforms ensures cross platform consistency. Calendar integration utilizes standard iCalendar protocol enabling compatibility with prevalent calendar applications. Testing confirmed successful scheduling, reminder delivery, and consultant notification across simulated user scenarios and calendar platforms. Interactive tutorials and guides provide multimedia educational content covering urban farming techniques. Content development prioritized practical techniques relevant to Indonesian urban contexts, including vertical farming methods, container gardening, pest management without synthetic pesticides, and water conservation strategies. Tutorial organization enables step by step guidance for specific crop types cultivated in urban environments. User engagement metrics during prototype testing revealed an average tutorial completion rate of 78%, indicating that multimedia educational approach successfully supports learning.

Analytics and reporting dashboard aggregates farm performance data across platform users. Visualization implements interactive charts displaying growth trajectories, yield projections, and comparative performance metrics. Customizable report generation enables users to extract specific metrics relevant to their farming objectives. Dashboard performance testing confirmed responsive visualization of datasets containing thousands of records, supporting scalability for growing user base. Integration testing across nine platform features confirmed seamless data flow supporting complete urban farming workflow. User pathway testing from initial planning through garden design, plant selection, health monitoring, expert consultation, and market linkage revealed no critical functional gaps. Prototype user testing with target demographic groups achieved 91% task completion rate across comprehensive workflow scenarios, indicating platform usability and functional completeness.

3.3 Comparison with existing urban farming solutions

Comparison of Urfalogy against existing urban farming platforms and technological solutions reveals several distinctive advantages. Unlike fragmented approaches addressing individual constraint dimensions, Urfalogy provides comprehensive integration addressing simultaneously technological, spatial, and economic barriers facing urban farmers. Existing platforms typically specialize in single domains such as pest detection, market linkage, or community knowledge sharing without providing integrated support across complete farming lifecycle. The integrated design philosophy of Urfalogy reflects theoretical understanding that urban farming constraints interact synergistically, requiring holistic solutions. Deep learning based spatial optimization represents a novel contribution not previously implemented in Indonesian urban farming contexts. Existing layout design approaches rely on manual recommendations or general principles without adapting to specific environmental characteristics of individual user spaces. The YOLOv8 based spatial optimization automatically analyzes unique environmental conditions, generating customized recommendations that maximize productivity within spatial constraints. This technological innovation directly addresses one of the three primary constraints limiting urban farming adoption in Indonesia (Amri, 2024).

Integration of IoT sensor technology for real time environmental monitoring exceeds capabilities of platforms relying on manual user reporting of farm conditions. Real-time monitoring enables immediate detection of conditions requiring intervention, supporting responsive farm management. Integration with expert consultation systems creates a decision support mechanism connecting automated monitoring with professional expertise. The E-commerce component of Urfalogy addresses economic barriers by reducing transaction costs for urban farmers by accessing input supplies and reaching consumer markets. Existing platforms typically focus on either supply-side or demand side connections without integration, requiring users to navigate multiple platforms. The integrated marketplace functionality simplifies transactions while building community of practice among urban farmers.

Comparison of performance metrics with related agricultural technology implementations validates effectiveness of the Urfalogy approach. The YOLOv8 model performance (mAP@0.5 0.90715) exceeds performance of agricultural object detection implementations reported in comparable studies, confirming technical rigor (Agustian et al., 2023; Suhas et al., 2024). Expert consultation integration and community functionality exceed capabilities of automated systems alone, reflecting human centered design principles that recognize importance of professional expertise and peer learning in agricultural decision making (Hakam, 2020).

3.4 Relationship between results and theoretical framework

The research findings demonstrate validation of core theoretical assumptions underlying Urfalogy development. First, deep learning algorithms prove effective for spatial optimization in constrained environments, confirming the hypothesis that artificial intelligence can address technological constraints in urban farming. The high performing YOLOv8 model provides empirical evidence supporting the theoretical expectation that machine learning can extract complex patterns from environmental data relevant to agricultural decision making. Second, the successful integration of nine diverse features within coherent platform architecture validates systems thinking approaches to addressing interconnected urban farming constraints. Results demonstrate that holistic platform design addressing technological, economic, and knowledge barriers simultaneously produces more effective solutions than fragmented approaches targeting individual constraints separately. This finding aligns with complex theory emphasizing emergent properties arising from integrated system components.

Third, positive user feedback and high task completion rates during prototype testing validate human centered design principles prioritizing accessibility and user experience. The platform's success in supporting complete urban farming workflow from planning through market linkage reflects theoretical understanding that technological tools must integrate with human decision-making processes and social networks rather than replacing them. Fourth, the platform's achievement of success metrics regarding deep learning performance, responsiveness, and user satisfaction validates the selection of Agile SDLC methodology. Iterative development enabling continuous user feedback and rapid refinement produced platforms substantially more aligned with user needs than linear waterfall approaches would have achieved. This empirical result corroborates theoretical advantages of agile methodology documented in software engineering literature (Afandi et al., 2023). The integration of findings across technical performance, feature functionality, and user experience demonstrates that Urfalogy successfully bridges technology development and practical application requirements. Results validate that integrated artificial intelligence and human expert systems can effectively support urban farming adoption in Indonesian urban contexts characterized by land scarcity, capital limitations, and technology access constraints.

3.5 Urban farming sustainability implications

The Urfalogy platform development and validation contributes to addressing fundamental challenges of urban food security in Indonesia. Successful implementation of AI powered spatial optimization, real time environmental monitoring, and integrated knowledge support systems provides a technological foundation for scaling urban farming beyond current limitations. The achievement of a high performing deep learning model and functional integration of nine platform features demonstrates technical feasibility of supporting urban agriculture through comprehensive technological systems. The platform's potential impact on three primary urban farming constraints warrants detailed analysis. First, the AI layout designer directly addresses spatial limitations by enabling optimization of constrained urban environments. By analyzing specific environmental characteristics including light intensity, ceiling height, and architectural features, the system enables productive agriculture in spaces that would otherwise remain unutilized. The 90.01% recall rate indicates that the system successfully identifies nearly all suitable agricultural spaces, minimizing opportunity loss.

Second, the integrated e-commerce functionality reduces capital barriers by connecting urban farmers with affordable input sources and premium market opportunities. By reducing transaction costs and enabling direct producer to consumer relationships, the platform improves economic returns on agricultural investment, making urban farming more financially attractive to prospective practitioners. This economic improvement addresses the youth participation barrier, as financial returns become more comparable to alternative livelihood opportunities. Third, the comprehensive knowledge support system combining automated analysis, expert consultation, and educational content addresses technological and knowledge barriers limiting urban farming productivity. By providing decision support for crop selection, health management, and environmental optimization, the platform reduces knowledge deficits that currently constrain urban farmer success rates. Integration with community knowledge networks builds social capital supporting collective learning and shared problem-solving.

Beyond addressing immediate constraint domains, Urfalogy contributes to broader sustainability objectives aligned with Sustainable Development Goal 11.3. The platform supports inclusive urbanization by enabling previously excluded urban residents to engage in productive food production. Participatory urban planning is enhanced through the data-driven design approach that incorporates user preferences and local environmental conditions rather than imposing generic solutions. The platform's capacity to support both individual farmer productivity and community knowledge networks demonstrates commitment to human development alongside technological advancement. The platform development experience provides lessons relevant to scaling urban agriculture across Indonesia. Technical feasibility of implementing advanced machine learning for agricultural optimization with locally available data has been demonstrated. The acceptance of technological solutions by target user populations, evidenced through high prototype engagement rates, indicates cultural compatibility beyond technical feasibility. The success of human centered design principles in creating accessible technology suggests that effective urban agriculture support systems must integrate technological capability with social and economic dimensions.

4. Conclusions

This research successfully developed and validated Urfalogy, an integrated artificial intelligence-powered platform addressing critical constraints limiting urban farming adoption in Indonesia. The primary contribution of this work lies in demonstrating that comprehensive technological systems combining deep learning-based spatial optimization, real-time environmental monitoring, expert consultation integration, and e-commerce functionality can effectively support sustainable urban agriculture in land-scarce urban environments. The achievement of a high performing deep learning model (mAP@0.5

0.90715, recall 0.90011) coupled with successful implementation of nine integrated platform features validates the technical feasibility and functional completeness of this approach. These results establish that artificial intelligence and human expert systems can work synergistically to overcome interconnected barriers of spatial limitation, capital insufficiency, and technological inadequacy that currently constrain urban farming in Indonesian cities.

The originality of this research extends beyond technical implementation to encompass systemic understanding of urban farming challenges. Unlike fragmented approaches addressing individual constraint dimensions, Urfalogy demonstrates that holistic platform design integrating technological, economic, and knowledge-support dimensions produces superior outcomes compared to single domain solutions. This system-level contribution reflects complexity theory principles emphasizing emergent properties arising from integrated components. The platform's successful integration of automated spatial analysis, real-time monitoring, expert consultation, community knowledge networks, and market linkage represents a paradigmatic shift in technological support for urban agriculture, positioning technology as enabler of human decision making rather than replacement for human expertise.

The implications for urban food security and sustainable development are substantial. By enabling productive agriculture in previously unutilized urban spaces, optimizing economic returns through market access, and reducing knowledge barriers through integrated expert consultation and educational systems, Urfalogy provides a technological foundation for scaling urban farming beyond current limitations. The platform's achievement of 91% task completion rate during user testing and 89% consultation satisfaction indicate strong user acceptance, suggesting cultural and practical viability of technology-enabled urban agriculture. This technological solution contributes directly to the achievement of Sustainable Development Goal 11.3 by supporting inclusive urbanization and participatory urban planning while enhancing food security and improving urban livelihood opportunities.

Future research directions include spatial expansion of platform validation to additional Indonesian cities and Southeast Asian contexts, longitudinal assessment of urban farmer outcomes including productivity and income improvements, integration of climate adaptation features supporting agricultural resilience in contexts of environmental variability, and investigation of community level impacts including food security outcomes and social capital development among urban farming networks. The successful development of Urfalogy provides the foundation for addressing persistent challenges of urban food systems while demonstrating broader applicability of integrated technology platforms to complex development challenges requiring simultaneous attention to technological, economic, and social dimensions.

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Author Contribution

Conceptualization, N.D. and A.I.W.; Methodology, N.D. and A.I.W.; Software, N.D.; Validation, N.D., A.I.W., and agricultural extension partners; Formal Analysis, N.D.; Investigation, N.D. and A.I.W.; Resources, A.I.W.; Data Curation, N.D.; Writing – Original Draft Preparation, N.D.; Writing – Review & Editing, A.I.W.; Visualization, N.D.; Supervision, A.I.W.; Project

Administration, N.D.; and Funding Acquisition, A.I.W. Both authors have read and agreed to the published version of the manuscript.

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Ethical Review Board Statement

Ethical review and approval were waived for this study because the research primarily involves technological platform development and deep learning model training using non sensitive environmental image datasets and voluntary user testing with informed consent. The research did not involve collection of personal health information, genetic data, or other sensitive personal information beyond standard user account information. User testing activities included informed consent procedures where participants voluntarily provided feedback on platform usability and functionality. All user data collected during prototype testing was handled according to data privacy principles with anonymous data aggregation for analysis. Therefore, formal Institutional Review Board (IRB) approval was not required under Indonesian research ethics guidelines for technology development research of this nature.

Informed Consent Statement

Informed consent was obtained from all subjects involved in user testing activities. Participants in focus groups and prototype testing were provided with clear information regarding research objectives, data collection procedures, and data privacy protections. Participants voluntarily agreed to provide feedback on platform functionality, usability, and perceived value. All participants were informed that participation was voluntary and could be discontinued at any time without penalty or loss of benefits. Written informed consent documentation was maintained for all research participants engaged in user testing activities.

Data Availability Statement

The Urfalogy platform prototype is accessible through the public interface at bit.ly/prototypeUrfalogy. Deep learning model is implemented using the open-source YOLOv8 framework available through the Ultralytics repository. Training datasets consisting of indoor environmental images are stored on secure institutional servers with access restricted to research team members and authorized collaborators due to privacy considerations regarding photograph collection from private residences. Aggregated performance metrics and quantitative results from deep learning model evaluation are presented in the manuscript. Inquiries regarding access to detailed training datasets or model weights should be directed to the corresponding author. Code for model training and platform implementation is available from the authors upon reasonable request subject to institutional policies on intellectual property and software licensing.

Conflicts of Interest

The authors declare no conflict of interest. The research was conducted independently without external funding, and no commercial interests influenced research design, data analysis, interpretation, or publication decisions. The software development framework and deep learning algorithms used in this research are open-source projects without proprietary restrictions. No authors have financial interests in any platform or technology development company that might benefit from this research. All potential conflicts have been carefully considered, and none were identified that would inappropriately influence the representation or interpretation of reported research results.

Declaration of Generative AI Use

During the preparation of this manuscript, the authors used AI writing assistance tools to support grammar improvement, clarity enhancement, and structural organization of technical content. Specifically, AI tools were utilized for: (1) refining academic writing tone and consistency across sections, (2) organizing technical descriptions of methodology in clear and logical sequence, (3) enhancing clarity of complex technical concepts for broader audience accessibility. After using these tools, the authors reviewed, edited, and substantially revised all content as needed, verified accuracy of all technical claims and citations, and took full responsibility for the content and integrity of the publication. All research findings, methodology, results, and conclusions represent the authors' original work and analysis, with AI tools serving only as writing assistance without influence on research design, analysis, or interpretations.

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