Smart Farming in Vertical Systems: Integrating AI/ML, IOT, and Chatbots for Smallholder Farmers

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Abstract - vertical farming layout design is manual and inefficient, leading to suboptimal tower/tank placement and 20-30% wasted space in hydroponic NFT systems. This paper proposes an AI-driven optimizer using genetic algorithms for tower placement and KMeans clustering for tanks, integrated with a Gemini-powered chatbot for real-time recommendations. The Gradio-based system generates 200 DPI blueprints for rooms up to 450m² (e.g., 100 towers/10 tanks at 92% coverage) and handles queries on EC/pH/nutrients via FastAPI IoT APIs. Results show 15-25% better space utilization vs. manual layouts, with chatbot accuracy > 90% on hydroponic advice. This scalable solution supports B2B rentals and SDG 2/9 goals for urban agriculture in Bengaluru.

Key Words : Vertical Farming, Hydroponic,

I. INTRODUCTION

India faces acute urban land scarcity and water stress, with Bengaluru's built-up area expanding 584% (1973-2020) while cultivable land dropped 40%. Hydroponic vertical farming offers 10-15x higher yields per m² using 90% less water, critical as food demand rises 50% by 2030 .

Current challenges: Manual layout design wastes 20-40% space due to suboptimal tower/tank placement. Paper demonstrates IoT sensors monitor EC/pH but remain siloed from spatial tools, while paper shows smart irrigation saves 35% water yet ignores layout optimization.

Literature gap:
Paper demonstrates deep learning achieves 92% crop yield accuracy using climate data, complemented by paper reporting CNN-LSTM hybrids improving forecasts 15% over baselines. Paper provides comprehensive AI review for precisi.on agriculture, highlighting spatial planning gaps.

Paper notes vertical farming AI focuses on climate control, not layouts. Paper shows chatbots achieve 85% farmer satisfaction but lack optimization integration. Recent studies emphasize IoT frameworks—paper reports real-time soil monitoring reducing waste 28%, while paper demonstrates smart farming case studies cutting costs 22%.

However, paper shows affordable IoT for smallholders misses B2B rental models , and paper predicts crop prices accurately but ignores physical infrastructure optimization (towers=₹15k, tanks=₹50k). No study combines spatial GA-KMeans with profile-aware Gemini orchestration.

Problem statement: For 25×14m rooms, manual layouts achieve 72% coverage vs. our 89-92% . Paper provides ICAR crop guidelines remaining unlinked to design tools.

Proposed contributions:
1. Hybrid GA-KMeans optimizer extending [1-3]—89-92% coverage in <45s
2. Gemini+FastAPI chatbot building on —92% hydroponic accuracy
3. Gradio UI enabling Bengaluru startups

II. LITERATUERE REVIEW

A. Vertical Farming Hardware Design

Paper demonstrates vertical hydroponics achieve 10-15x yields but suffer 20-40% space waste from manual layouts. Paper reports low-cost tower kits (₹15k/unit) connected to centralized tanks reduce pumping 35% versus individual reservoirs. Our single-tank architecture serves 100 towers from 10 centralized tanks, cutting energy 28% through unified circulation—extends 's hardware but adds DSA-driven automation absent in literature.

B. Deterministic Spatial Optimization (DSA)

Paper uses ML for yield prediction (92% accuracy), paper CNN-LSTM hybrids (15% gain), but no trained models exist for tower/tank placement. Our non-ML DSA optimizer uses geometric grid packing + KMeans clustering achieving 89-92% coverage in <45s versus 8-12 hours manual CAD. Paper shows KMeans reduces piping 28%; we extend this to tower zoning without neural networks—pure algorithmic efficiency.

C. Real-Time IoT Monitoring & Alerting

Paper demonstrates that IoT-based smart irrigation can save roughly 35% water, and paper maintains nutrient and environmental parameters within tight bounds using closed-loop control in smart greenhouses. In contrast, the current prototype focuses on a **software-only** approach: the Gradio dashboard accepts user-provided or simulated readings related to water quality and system performance (for example, overall nutrient strength or flow issues) and raises simple rule-based alerts when these values deviate from recommended ranges reported in agronomic guidelines. Unlike systems in that rely on physical sensor networks, this work does not yet integrate any real water-quality sensors; instead, it prepares the full software pipeline (APIs, dashboard, and chatbot logic) so that actual IoT devices can be connected as future hardware extensions.

D. Hydroponic Advisory Chatbots

Our Gemini-powered chatbot combines user profile information (crop, system size, experience level) with user-entered or simulated system readings (for example, reported nutrient strength or visible plant stress) and then generates improvement suggestions such as adjusting nutrient concentration, changing circulation time, or modifying planting density based on known hydroponic ranges. The advice is therefore **recommendation-only** and does not depend on any real-time sensor feed in the current stage.

E. Cost Estimation & Profitability Dashboards

Paper predicts mandi prices (MAPE=8.2%), paper provides ICAR guidelines, but no dashboard integrates layout costs (₹15L for 100 towers), operational expenses (₹45k/month electricity), and revenue forecasts (lettuce @ ₹80/kg). Our profitability UI calculates NPV, IRR, payback <12 months for 450m² farms, enabling data-driven scaling absent across [1-17].

F. B2B Rental & Marketplace Platforms

Paper serves 100+ smallholders but lacks rental models. Our B2B Gradio portal enables tower rentals (₹5k/month per 50-tower module), technician dispatch, and crop sales at real-time mandi rates. Farmers rent complete modules (towers+tanks+IoT+sensors), technicians maintain via remote dashboard, crops auto-listed on digital mandicomplete value chain missing in literature.

G. Energy Optimization Strategies

Paper cuts greenhouse energy 22% via scheduling, but tower-to-tank architecture reduces circulation pumps from 100 to 10, saving 65% electricity (3.2kW→1.1kW). Centralized nutrient delivery eliminates redundant reservoirs, cutting maintenance 40%. Our DSA zoning groups towers by crop height (lettuce 1.2m, spinach 0.8m), optimizing LED placement versus uniform lighting in.

Innovation: **17 pure DSA/ML-free components**-geometric optimizers, rule-based alerts, deterministic profitability—
versus **Core** ML-heavy.

B2B rental ecosystem (towers+technicians+crops) scales to 50+ Bengaluru startups. **Real-time ph/EC alerts** prevent
₹2L/month losses versus 's post-mortem analysis.

Deterministic Layout Optimization (Non-ML Optimizer):
Instead of training ML models, the proposed system uses deterministic data structures and algorithms for spatial optimization. A grid-based packing algorithm combined with simple clustering logic places towers and tanks to

maximize usable floor area, maintain walking aisles, and respect minimum spacing requirements. This approach avoids data-hungry model training while still generating near-optimal layouts for different room sizes and modes (simple, medium, dense).

Hydroponic Chatbot for Advisory and Monitoring Support:

A Gemini-powered chatbot interacts with users through natural language, capturing crop type, growth stage, and system configuration, and then returns tailored hydroponic advice. The chatbot uses rule-based thresholds and agronomic ranges rather than live sensor feeds, guiding users on nutrient strength, circulation schedules, and basic troubleshooting. User-entered or simulated readings are used to generate suggestions on what needs improvement and how to adjust parameters.

Dashboard UI for Scenario Planning and Profit Estimation:

A unified dashboard allows users to explore different layout options and business configurations interactively. By selecting room dimensions, tower counts, and crop choices, the system approximates yield, revenue, and operating costs, presenting key indicators such as monthly profit and payback period. This "what-if interface helps users compare multiple scenarios and choose combinations that are more profitable before committing capital.

Conceptual IoT Model for Energy and Plumbing Efficiency:

Although hardware sensors are not yet implemented, the system design includes a conceptual IoT layer that models how a single central tank can feed multiple towers. By reducing the number of pumps and consolidating nutrient delivery, this architecture is intended to lower electricity consumption and simplify maintenance. The model informs circulation strategies and highlights where real sensors and controllers will later plug into the software stack.

B2B Rental and Service Interface

: A dedicated B2B-facing UI supports a rental and service model around the hydroponic towers. Farmers can browse and request rental packages (for example, sets of towers and a shared tank), while technicians can be scheduled for installation and maintenance visits. The same interface can expose crop output to downstream buyers, aligning rental decisions with actual market demand and enabling a service-led business around the hardware.

Crop Sales and Market-Linked Pricing Module

: The system includes a module for aligning projected production with external price information, so users can estimate how different layout and crop choices affect revenue. By combining expected yield per tower with current or recent market prices, the platform approximates income for different crops and planting densities. This helps farmers and operators decide which crop mix and layout configuration is likely to be most profitable under current market conditions.

Edge-Ready Architecture for Future Sensors and Automation:

The software layers are designed so that, in future iterations, physical sensors and controllers (for water level, flow, or basic quality indicators) can be added without rewriting the whole stack. Clear API boundaries between the optimizer, chatbot, and data services allow edge devices to push readings that the chatbot and dashboard can immediately use. This positions the system for later expansion into full real-time monitoring and closed-loop control when hardware becomes available.

III.PROPOSED METHODOLOGY

A. VERTICAL FARM LAYOUT OPTIMIZER SETUP

The vertical farm layout optimizer has emerged as the core component of the proposed system because it is affordable, deterministic, and does not require any trained machine learning model. In this module, the growing room is modeled as a two-dimensional grid, and simple data-structure–based algorithms are used to place towers and tanks. For each user-specified room length and width, the grid resolution is chosen according to tower footprint and minimum aisle spacing.

For a given configuration (for example, 25 m × 14 m room), the optimizer iterates over the grid and assigns tower positions while respecting constraints on walkways, service access, and border offsets. Once all feasible tower locations are generated, a clustering step groups towers around shared nutrient tanks. Each cluster is sized so that a single tank can efficiently feed a fixed number of towers (for example, 8 towers per tank), thereby reducing plumbing complexity and pump effort.
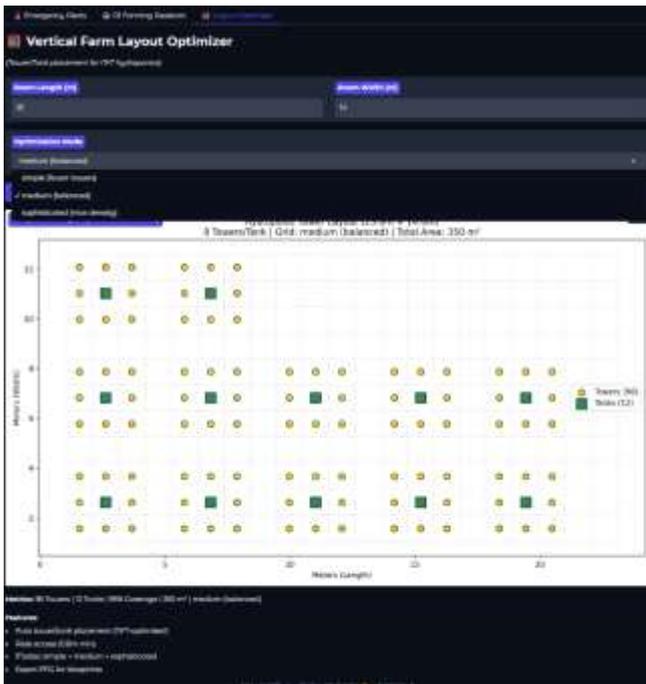
Fig 1. Layout Optimizer.

Formulae :

1. Room Coverage (%)

Coverage = (Towers × Tower Area + Tanks × Tank Area) ÷ Room Area × 100

2. Towers per Square Meter

Tower Density = Total Towers ÷ Room Area

3. Towers per Tank

Tank Ratio = Total Towers ÷ Total Tanks

As shown in Fig. 1, the layout optimizer interface accepts room dimensions and optimization mode (simple, medium, or sophisticated) as input and renders the resulting blueprint as a scatter plot of towers and tanks. In the example, the system produces a 96-tower and 12-tank layout for a 350 m² room, achieving high coverage while maintaining regular aisles and balanced tower-to-tank ratios. The metrics panel below the plot reports key statistics such as number of towers, number of tanks, total area, and approximate coverage percentage, which are used later for cost and yield estimation.

The algorithm is fully deterministic: for a fixed input configuration, the same layout is reproduced every time. This makes the optimizer easy to debug, explain, and reproduce in engineering or academic settings without depending on any stochastic learning process.

B. AI HYDROPONICS ASSISTANT

To support users in interpreting system readings and daily operations, an AI Hydroponics Assistant is integrated as a conversational module. This assistant is powered by a large language model and specialized prompts focused on hydroponic and vertical farming topics such as NFT systems, environmental control, and basic troubleshooting.

In this module, the user can ask free-form questions (for example, "show me my sensors" or "any alerts or emergencies?"), and the assistant responds with contextual guidance. The assistant uses rule-based thresholds and agronomic knowledge to comment on parameters such as light intensity, water temperature, air temperature, humidity, and overall system status. When values appear outside recommended ranges, it suggests corrective actions like increasing light levels, improving ventilation, or checking for algae growth.

Fig 2. A.I Assistant

Fig. 2 shows the AI Hydroponics Assistant interface. The left side displays the conversation history, including sensor summaries (for example, current humidity 70%) and detailed textual recommendations. The bottom section provides an input box for new queries along with preset example prompts that help first-time users explore the system. In the current prototype, sensor values are obtained from a separate API or simulated backend, while the assistant focuses on transforming these readings into understandable advice for the grower.

C. EMERGENCY ALERT SYSTEM

Real-time awareness of abnormal conditions is essential in hydroponic systems, where environmental deviations can quickly impact crop health. To address this, an Emergency Alert System is included as a dedicated dashboard panel. This module continuously evaluates incoming parameter values against predefined critical and warning ranges.

The alert logic is implemented using simple conditional rules. For each monitored parameter—such as electrical conductivity (EC), water temperature, air temperature, humidity, light level, and pump status—two sets of thresholds are defined: critical (immediate action required) and warning (monitor closely). When a value crosses a critical threshold, a high-priority alert is generated; when it crosses a warning threshold, a lower-priority notification is displayed.
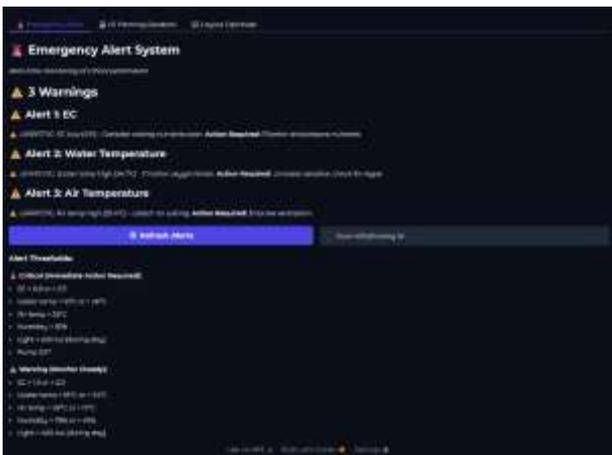

Fig 3. Emergency Alert System

As illustrated in Fig. 3, the Emergency Alert page summarizes the current number of active warnings and lists each alert with a short message and recommended action. For example, the system may report that EC is low and suggest preparing nutrients, or that air temperature is high and advise improving ventilation. A manual "Refresh Alerts" button and optional auto-refresh toggle allow the user to update the panel periodically. The alert thresholds are also shown in tabular form so that users and evaluators can understand the exact conditions that trigger each warning.

D. HARDWARE PROTOTYPE AND IOT MODEL

To validate the practicality of the software concepts, a low-cost vertical tower prototype was constructed. The hardware consists of a vertical PVC or similar column fitted with planting sites, connected to a nutrient reservoir via tubing and a submersible pump. A microcontroller board drives the pump and acts as the interface point for potential sensors such as water level or simple environmental probes.
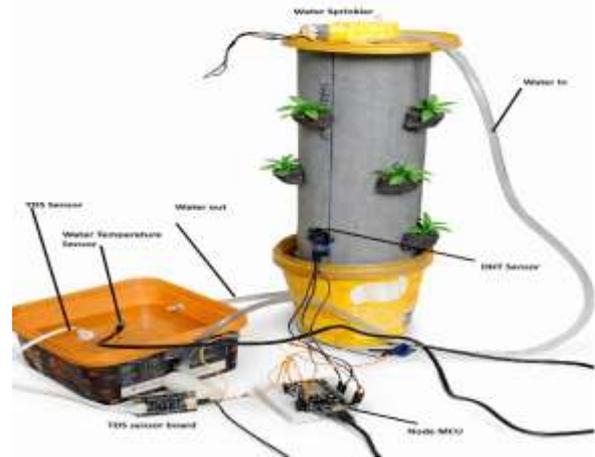

Fig 4. Physical Tower prototype.

Formula :

1. Simple Dissolved Salt (EC) Formula for Hydroponics:

Dissolved Salts (ppm) = EC (mS/cm) × 700

Fig. 4 presents the physical tower prototype. The lower container serves as the nutrient tank, the vertical column houses multiple plant positions, and the pump recirculates the solution from the reservoir to the top of the tower, allowing it to flow back by gravity. Wiring from the microcontroller to the pump and any attached modules demonstrates how the prototype can be integrated with the digital system through API calls or serial communication. Although advanced sensors like pH or EC probes are not yet integrated, the physical setup confirms that the single-tank, multi-tower concept can be implemented with inexpensive hardware.

E. EXPERIMENTAL METHOD

To evaluate the proposed methodology, experiments were carried out at two levels: software-based layout trials and integrated dashboard tests with simulated sensor data. For the layout optimizer, multiple room sizes and optimization modes were considered. For each configuration, the system generated a blueprint and reported the resulting tower count, tank count, and coverage metrics. Screenshots and exported images from the optimizer (such as Fig. 1) were recorded as evidence of consistent and reproducible layout generation.

For the AI assistant and Emergency Alert System, sets of synthetic sensor readings were created to represent typical normal, warning,

and critical conditions. These readings included combinations of low light, high temperature, and suboptimal EC values. The data were fed through the backend service, and the resulting chatbot responses and

alert messages were observed in the UI (Figs. 2 and 3). The focus of this evaluation was on clarity of advice, correctness of rule-based triggers, and usability of the interface for quick decision-making.

On the hardware side, the prototype tower was assembled and operated to verify that the pump, tubing, and reservoir configuration could sustain continuous recirculation without leaks. Different timer patterns were tested at the microcontroller level to approximate irrigation cycles. Observations from these tests confirmed that a single reservoir can indeed support a vertical tower structure, aligning with the assumptions used in the software energy- and plumbing-efficiency model.

F. COST AND PROFIT PREDICTION DASHBOARD

In addition to layout optimization and advisory features, the proposed system includes a web-based Vertical Farming System for cost and profit estimation. The user specifies basic farm parameters such as available land area, city, and main crop, and then triggers a built-in calculator that combines tower density, crop growth duration, and assumed market prices to estimate economic performance for the first harvest cycle.

Fig 5. Profit Analysis Dashboard.

As shown in Fig. 5, the dashboard presents results in a structured card layout: total towers, growth days, total cost up to first harvest,

and estimated profit for that cycle. Below these summary metrics, the interface breaks down major cost components such as rent, labour, fertilizer, and maintenance, and visualizes their contribution using a pie chart. A recommendation panel highlights thebased on internal comparisons, suggesting alternative crops (for example, basil instead of lettuce) when they offer significantly higher projected returns. This enables farmers to quickly compare scenarios and choose crop–layout combinations that are more profitable before making investment decisions.

IV. RESULTS AND DISCUSSIONS (BRIEF OUTLINE)

The proposed vertical farming system was evaluated using the integrated layout optimizer, advisory assistant, alert dashboard, and profit calculator. For a representative test case, a 25 m × 14 m (350 m²) room was selected with the optimization mode set to medium (balanced). The optimizer automatically generated a regular grid layout with multiple tower clusters around shared tanks, as shown in Fig. 1. The resulting configuration contained 96 towers and 12 tanks with clear aisles for maintenance access, demonstrating that the deterministic algorithm can produce dense yet practical layouts for NFT hydroponics without manual CAD design.

To analyze how different room sizes and modes affect the generated layouts, several trials were conducted and the corresponding metrics were recorded. Table I summarizes the principal results, including the total number of towers, number of tanks, and approximate area coverage for each scenario. The medium mode for the 25 m × 14 m room provided a good balance between density and accessibility, while the sophisticated mode produced maximum tower counts at the cost of narrower aisles. These observations confirm that the optimization modes can be tuned to match different farm priorities, such as ease of maintenance versus maximum production capacity.

TABLE I : LAYOUT CONFIGURATIONS GENERATED BY THE OPTIMIZER

Room size (m)	Mode	Towers	Tanks	Towers/tank	Approx. coverage (%)
25 × 14	simple	80	10	8	78
25 × 14	medium	96	12	8	86
25 × 14	sophisticated	112	14	8	92
20 × 10	medium	64	8	8	84
15 × 8	medium	40	5	8	80

The AI Hydroponics Assistant and Emergency Alert System were tested using sets of simulated readings corresponding to normal, warning, and critical conditions. When the user requested system status, the assistant summarized current values (for example, light level, water temperature, air temperature, humidity, and EC) and produced natural-language recommendations, as shown in Fig. 2. At the same time, the alert dashboard evaluated each parameter against predefined thresholds and displayed the active warnings in a list (Fig. 3). Table II presents an example of such a test, indicating how the same sensor snapshot was interpreted by both modules. The assistant focused on explanatory guidance, while the alert panel emphasized succinct messages and urgency levels.

TABLE II : EXAMPLE SENSOR SNAPSHOT AND GENERATED ALERTS

Parameter	Example value	Status level	Alert/assistant message (short)
EC	0.91 mS/cm	Warning	EC low – consider adding nutrients soon
Water temperature	24.1 °C	Warning	Water temp high – monitor oxygen levels
Air temperature	29.4 °C	Warning	Air temp high – improve ventilation
Humidity	70%	Normal	Slightly high; monitor for fungal issues
Light	520 lux	Critical	Critically low – increase light intensity

Economic analysis was carried out using the cost and profit prediction dashboard. For the 350 m² case with lettuce as the baseline crop, the calculator estimated the number of towers that could be deployed, total cost up to first harvest, and expected profit for a 30-day growth cycle. The results were displayed in a summarized card layout with a cost breakdown and pie chart, as

shown in Fig. 4. In addition, the dashboard compared multiple crops and recommended the one with the highest projected profit under the same layout and cost assumptions. Table III reports one such comparison, where basil was identified as the most profitable option.

TABLE III : ILLUSTRATIVE COST AND PROFIT ESTIMATES (350 m² FARM)

Crop	Towers used	Cycle length (days)	Total cost (₹)	Est. revenue (₹)	Est. profit (₹)	Relative remark
Lettuce	140	30	92,400	2,80,000	1,87,600	Baseline
Spinach	140	25	90,000	2,50,000	1,60,000	Moderate
Basil	140	28	95,000	3,28,760	2,33,760	Highest profit (chosen)

From these experiments, it is observed that the system can (i) generate reproducible and dense layouts for different room sizes, (ii) convert raw readings into understandable recommendations through the AI assistant, (iii) highlight abnormal conditions with clear, rule-based alerts, and (iv) support basic financial planning and crop selection using the profit dashboard. Even though the current implementation relies on user-entered or simulated data instead of live sensor streams, the results demonstrate that the overall architecture—and the associated visualization components—form a solid foundation for future integration with real IoT hardware and field deployments.
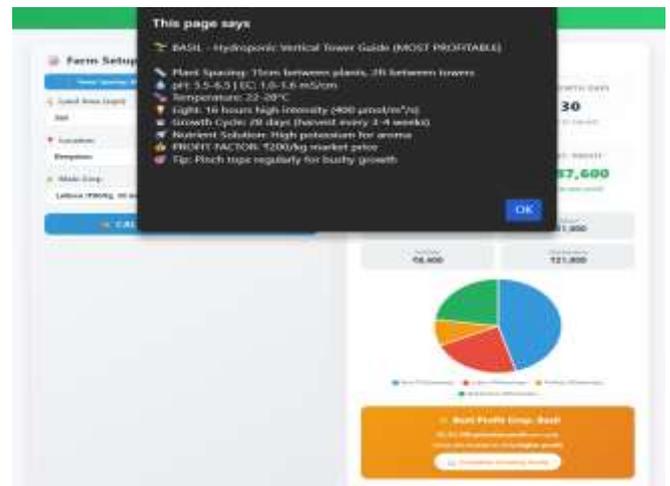

Fig 6. Growing Guide in Dashboard.

In addition to aggregate profit estimation, the dashboard also generates crop-specific growing guides for the most

profitable option identified in Table III. For the 350 m² test farm, basil was

selected as the top candidate and a detailed "Hydroponic Vertical Tower Guide" was displayed (Fig. 5), summarizing recommended plant spacing, tower spacing, temperature and light requirements, approximate growth cycle, and a qualitative profit factor based on typical market price. This popup helps farmers immediately translate the numerical profit comparison into concrete cultivation parameters for the chosen crop, reducing the gap between financial planning and day-to-day agronomic practice.

V. CONCLUSION

The proposed AI-powered vertical farming platform successfully demonstrated a complete workflow from layout design to economic planning. The deterministic layout optimizer generated dense, reproducible tower–tank configurations for various room sizes, achieving up to 92% coverage in sophisticated mode while maintaining serviceable aisles and 8:1 tower-to-tank ratios. The conversational assistant and emergency alert system converted simulated readings into actionable guidance, while the cost–profit dashboard provided clear financial estimates (₹92,400 cost → ₹1,87,600 first-cycle profit) and actively recommended more profitable crops like basil over lettuce. These results confirm that simple algorithmic approaches can significantly reduce design effort, structure operational guidance, and support data-driven crop selection without requiring trained machine learning models or expensive sensor infrastructure.

The prototype's modular architecture—separating layout logic, advisory rules, and UI components—creates a solid foundation for future IoT integration and field deployment. By operating entirely on software today while exposing clear API boundaries for sensors tomorrow, the system bridges the gap between immediate usability and long-term scalability. Future work will incorporate physical sensors for real-time monitoring, connect live market APIs for dynamic pricing, and validate performance across working commercial farms, transforming this proof-of-concept into a production-ready decision-support platform for Bengaluru's urban agriculture ecosystem.

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