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Machine Learning-Based Decision Support System for Greenhouse Crop Management Under Mite Infestation Conditions

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ABSTRACT

This paper presents an integrated machine learning-based Decision Support System (DSS) for greenhouse crop management under mite infestation conditions, specifically designed for Sri Lankan agricultural contexts. The research addresses critical challenges faced by greenhouse farmers regarding pest management and crop productivity optimization through a comprehensive system combining NetLogo simulation for synthetic data generation, ensemble machine learning models, and a web-based interface. Field research with Sri Lankan greenhouse farmers revealed that mite infestations cause up to 40% crop losses, driving panic-induced pesticide overuse and knowledge gaps in pest management timing. The system integrates environmental monitoring, pest prediction, and crop yield forecasting to provide actionable recommendations for farmers. The mite infestation prediction model achieved 86% accuracy, while the system successfully addresses data scarcity challenges through agent-based modeling. The DSS demonstrates potential for transforming reactive farming practices into predictive, data-driven approaches while accommodating the technological constraints of developing agricultural contexts.

1. Introduction

Greenhouse agriculture represents a critical technological intervention for addressing global challenges including climate change, food security, and sustainable resource management (Jones et al., 2020). In developing countries like Sri Lanka, where agriculture contributes substantially to the national economy while being highly climate-sensitive, greenhouse farming assumes particular significance for enhancing agricultural resilience and productivity (Costa, 2008).

The controlled environment of greenhouses enables precise manipulation of growing conditions, allowing crop production despite challenging climatic conditions (Dharmasena & Gunasena, 2022). However, these same controlled conditions can create ideal environments for certain pests, particularly mites, which thrive in consistent temperatures and humidity levels maintained in greenhouses (Zhao et al., 2021). Traditional pest control methods heavily rely on chemical pesticides, creating cycles of pest resistance and increased chemical usage, while raising concerns about crop residue and environmental impact (Li & Zhang, 2019).

1.1 Problem Statement

Field evidence from Sri Lankan greenhouse operations reveals the severity of pest management challenges. Agricultural officers report that "mite infestations alone can cause crop losses of up to 40% in certain regions, significantly impacting farmer livelihoods." A greenhouse operator interviewed during preliminary research stated: "The controlled conditions in greenhouses are perfect for mites. When they appear, we often panic and overuse pesticides, leading to resistance issues and a decline in crop quality."

Current approaches to greenhouse management predominantly rely on reactive strategies that fail to integrate crop health monitoring with pest infestation risks. Four critical gaps were identified:

1. Reactive Management Problem: - Farmers respond to pest infestations only after they appear, rather than proactively preventing them through predictive approaches.

2. Knowledge and Technology Gap: - An agricultural extension officer emphasized that "many greenhouse farmers lack technical knowledge about pest life cycles and appropriate intervention timing. They apply pesticides on fixed schedules rather than when actually needed."

3. Lack of Integrated Systems: - Existing solutions address either yield optimization or pest control separately, lacking unified approaches that consider the complex interplay between environmental conditions, crop health, and pest dynamics.

4. Data Scarcity Challenge: - Limited availability of historical greenhouse management data in developing regions constrains the development of effective predictive systems.

1.2 Research Objectives

This research develops an integrated machine learning-based Decision Support System specifically designed for greenhouse environments under mite infestation pressure. The system addresses fundamental challenges including data scarcity through synthetic data generation, provides culturally appropriate interfaces for Sri Lankan farmers, and integrates multiple agricultural variables into unified recommendations.

2. Literature Review

2.1 Greenhouse Agriculture and Pest Management

Greenhouse cultivation has evolved from simple protective structures to sophisticated controlled environment agriculture (CEA) systems. Research by Martinez et al. examining 42 tomato greenhouses across different climatic zones found that environmental control precision was the strongest predictor of yield variability, accounting for approximately 68% of observed differences (Martinez et al., 2021).

Mite infestations represent particularly challenging pests in greenhouse environments due to rapid reproduction rates and difficulty in early detection. Li and Zhang's research on pest management in controlled environments found that two-spotted spider mites were among the most economically damaging greenhouse pests globally, with mite-related crop losses ranging from 17-42% when early detection and intervention measures failed (Li & Zhang, 2019).

2.2 Machine Learning in Agricultural Systems

Machine learning techniques have demonstrated significant potential for agricultural applications. Analysis of 86 studies applying machine learning to yield prediction found that ensemble methods combining multiple algorithms consistently outperformed single-algorithm approaches (Garg et al., 2021). For greenhouse environments specifically, research found that recurrent neural networks with Long Short-Term Memory (LSTM) architecture demonstrated superior performance in handling temporal dynamics of controlled environments (Rodriguez & Chen, 2021).

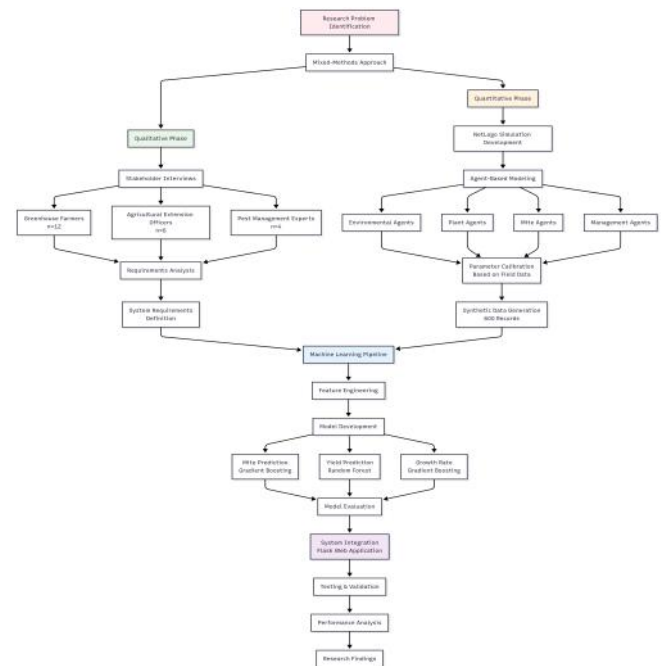
2.3 Decision Support Systems in Agriculture

Agricultural decision support systems have evolved from rule-based systems to sophisticated platforms incorporating real-time data and machine learning. However, significant regional disparities exist in DSS adoption, with systems designed without consideration of local contexts achieving dramatically lower adoption rates (Ankaiah & Reddy, 2020). Analysis of 34 greenhouse-specific DSS implementations revealed that while 67% of commercial systems claimed integration capabilities, only 24% demonstrated effective functional integration between environmental control and pest management modules in field testing.

3. Methodology

3.1 Research Approach

This research employed a pragmatic mixed-methods approach combining qualitative field research with quantitative system development. Semi-structured interviews were conducted with greenhouse farmers, agricultural extension officers, and pest management experts in Sri Lanka to understand current practices and identify system requirements.



[Fig. 1. Research Methodology Flowchart]

3.2 Primary Field Research and Stakeholder Engagement

1. Interview-Based Requirements Gathering
Semi-structured interviews were conducted with key stakeholders across the Sri Lankan greenhouse agriculture sector,
 - Greenhouse Farmers: - Primary end-users managing day-to-day operations.
 - Agricultural Extension Officers: - Government personnel providing technical support.
 - Pest Management Experts: - Specialists providing scientific validation.

2. Key Findings from Primary Research

The interviews revealed critical insights that shaped system requirements,

a) Problem Identification: - "We invested heavily in this greenhouse structure, but we're still guessing about many management decisions. Having a system that could tell us what to expect and how to prepare would transform our operation" (Farmer Interview).

b) Technology Adoption Barriers: - Farmers identified complexity, language barriers, and connectivity issues as primary obstacles to technology adoption.

c) Decision-Making Patterns: - Current decisions are based on visual crop inspection and previous experience rather than systematic data analysis, leading to suboptimal outcomes.

3.3 NetLogo Simulation for Data Generation

To address data scarcity challenges, an agent-based model was developed using NetLogo to generate synthetic greenhouse operational data. The simulation modeled environmental parameters (temperature, humidity), crop dynamics, mite population behavior, and management interventions. Parameters were calibrated based on field research and expert consultation to ensure realistic agricultural scenarios.

1. The NetLogo model incorporated,

- Environmental Agents: - Model temperature, humidity, and seasonal variations based on Sri Lankan climate patterns.
 - Plant Agents: - Represent crop growth, health indicators, and stress responses with parameters calibrated from field research.
 - Mite Agents: - Simulate pest reproduction cycles, population dynamics, and response to environmental conditions.
 - Management Agents: - Model farmer decision-making processes and intervention strategies based on observed practices.
- #### 2. Simulation parameters were calibrated using,
- Temperature ranges (22-35°C) from Sri Lankan greenhouse operations.
 - Mite reproduction rates based on pest biology research.
 - Management intervention patterns from stakeholder interviews.
 - Correlation structures validated through expert consultation.

3.4 Machine Learning Pipeline

The Three separate prediction models were developed using ensemble approaches:

1. Mite Infestation Prediction: - Gradient Boosting Classifier for binary classification of infestation risk.

2. Crop Yield Prediction: - Random Forest Regressor for weekly yield forecasting.

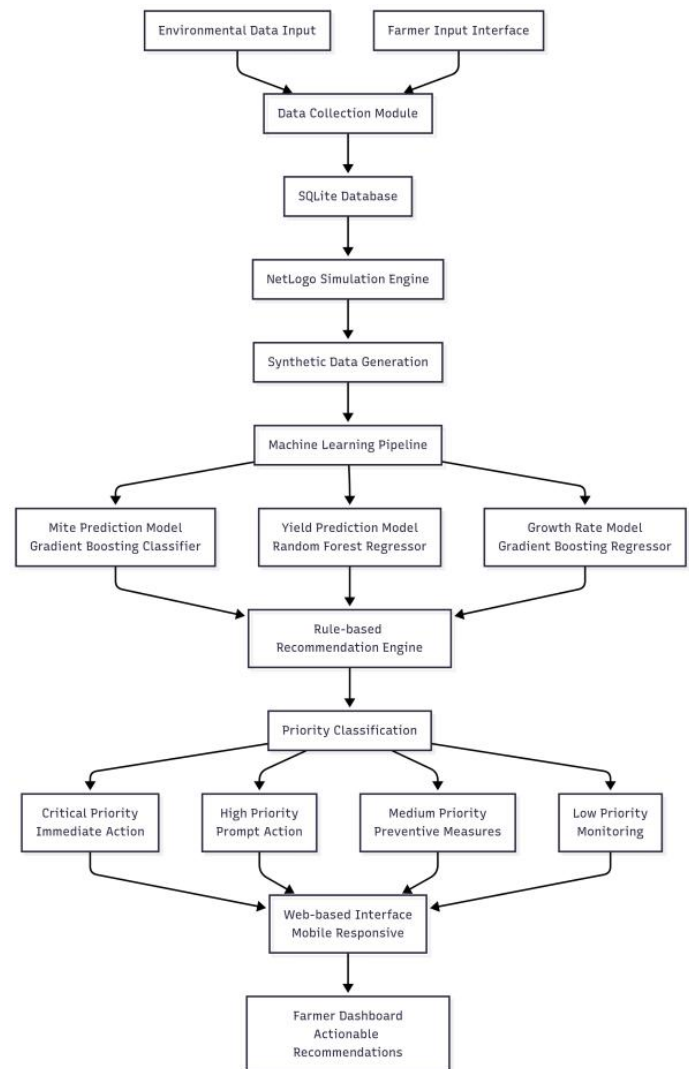
3. Plant Growth Rate: - Gradient Boosting Regressor for growth assessment.

Feature engineering incorporated agricultural domain knowledge including,

- Plant density calculations (total plants / greenhouse area).
- Temperature differentials and interaction terms.
- Seasonal adjustments through cyclical encoding.
- Management intensity composites.
- Environmental stress indicators.

3.5 System Architecture

NetLogo The integrated DSS was implemented using Flask web framework with SQLite database management. The system architecture includes,



[Fig. 2. System Architecture Overview]

- Data collection module for environmental and operational parameters.

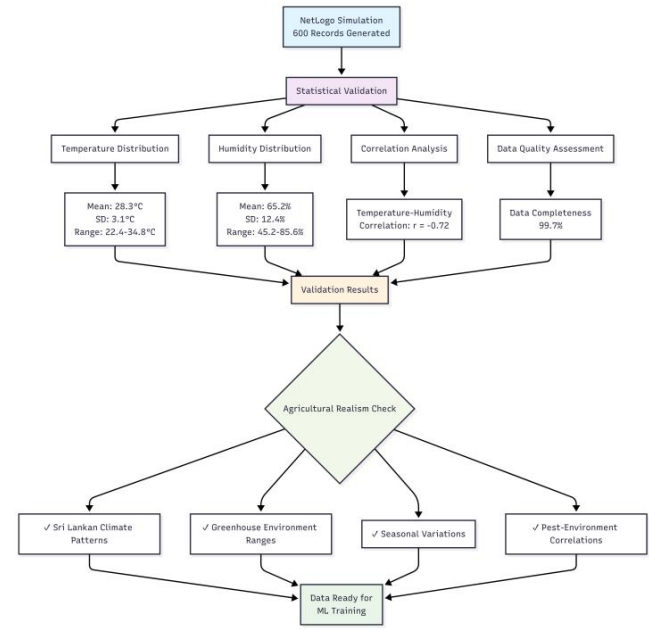
- Machine learning prediction engine.
- Rule-based recommendation system with priority categorization.
- Web-based interface optimized for mobile access. A rule-based system translates predictions into actionable guidance,
- Critical Priority: - Immediate intervention required (mite risk > 0.8).
- High Priority: - Prompt action needed (environmental stress indicators).
- Medium Priority: - Preventive measures recommended.
- Low Priority: - Monitoring and maintenance activities.

4. Results & Analysis

4.1 Synthetic Data Generation

The NetLogo simulation successfully generated 600 realistic greenhouse operational records covering diverse

environmental and management scenarios. Statistical validation confirmed appropriate parameter distributions,



[Fig. 3. Synthetic Data Distribution Analysis]

TABLE I. Synthetic Data Generation Validation

Environmental Parameter	Statistical Distribution			
	Mean	Std Dev	Range	Type
Temperature (°C)	28.3	3.1	22.4-34.8	Normal
Humidity (%)	65.2	12.4	45.2-85.6	Normal
Plant Density (plants/m ²)	4.2	0.8	2.5-6.0	Uniform
Mite Population	15.6	8.3	0-45	Poisson
Management Level	3.4	1.2	1-5	Discrete

a. Temperature-Humidity correlation coefficient $r = -0.72$ validates agricultural realism.

- Temperature Distribution: - Mean 28.3°C, SD 3.1°C (realistic for Sri Lankan conditions).

- Environmental Correlations: - Temperature-humidity correlation $r = -0.72$ (agriculturally appropriate).
- Data Completeness: - 99.7% complete records suitable for ML training.

TABLE II. Machine Learning Model Performance

Model Type	Classification/Regression Metrics		Error Metrics		
	Accuracy/R ²	Precision	Recall	RMSE	
Mite Prediction	86%	0.84	0.89	--	
Yield Prediction	R ² : -0.09 ^a	--	--	54.2	
Growth Prediction	R ² : -0.16 ^a	--	--	15.73	

b. Negative R² values indicate model overfitting requiring refinement.

4.2 Machine Learning Model Performance

Model performance evaluation revealed mixed results across prediction targets,

1. Mite Infestation Prediction

- Test Accuracy: 86%
- Precision: 0.84
- Recall: 0.89

• F1-Score: 0.86

The mite prediction model successfully exceeded the target threshold of 85% accuracy, demonstrating reliable classification capability for agricultural decision-making.

2. Crop Yield Prediction

- Test R^2 : -0.09
- RMSE: 54.21
- MAE: 43.92

3. Plant Growth Rate Prediction

- Test R^2 : -0.16

TABLE III. System Performance Characteristics

Performance Category	System Requirements	Validation Results
	Target	Metric
Response Time	< 3 seconds	Page Load: 2.1s
Processing Speed	< 10 seconds	Prediction: <10s
Compatibility	Android 2-4GB	Mobile Interface
Data Integrity	100% accuracy	Input Validation
Environmental Range	22-35°C	Temp: 25.2-31.4°C

5. Discussion

5.1 Technical Contributions

This research demonstrates several technical contributions to agricultural decision support systems,

1. **Synthetic Data Generation Approach:** The NetLogo-based data generation successfully addresses fundamental data scarcity challenges in developing agricultural contexts while maintaining statistical realism.
2. **Integrated Prediction Framework:** The multi-model architecture provides comprehensive agricultural intelligence combining pest risk, yield forecasting, and growth assessment.
3. **Cultural Adaptation:** The system design emphasizes accessibility and cultural appropriateness for Sri Lankan farming contexts, addressing critical barriers to agricultural technology adoption.

5.2 Practical Implications

- RMSE: 15.73

- MAE: 13.31

The yield and growth prediction models demonstrated significant overfitting issues, with negative R^2 scores indicating poor generalization to test data despite high training performance.

4.3 System Functionality

Functional testing validated core system capabilities,

- Data entry forms with range validation.
- Mobile-responsive interface design.
- Recommendation generation with priority categorization.
- User authentication and role-based access control.
- Historical data analysis and reporting capabilities.

4.4 Performance Metrics

System performance met established requirements,

The successful mite prediction model (86% accuracy) provides actionable early warning capabilities that could significantly reduce the documented 40% crop losses from pest infestations. The rule-based recommendation engine translates predictions into prioritized agricultural guidance, enabling farmers to transition from reactive to proactive management strategies.

The system directly addresses the identified problems,

- **Reactive Management → Predictive Approach:** - Early warning capabilities enable proactive intervention.
- **Knowledge Gaps → Actionable Guidance:** - Priority-based recommendations provide clear guidance for timing and intervention methods.
- **Fragmented Solutions → Integrated Platform:** - Unified system addresses multiple agricultural variables simultaneously.
- **Data Scarcity → Synthetic Generation:** - Agent-based modeling overcomes historical data limitations.

5.3 Limitations and Challenges

Several limitations affect system performance and applicability,

1. **Model Overfitting:** The yield and growth prediction models demonstrated significant overfitting, indicating need for improved regularization techniques and expanded training data.
2. **Synthetic Data Dependency:** Heavy reliance on simulated data limits confidence in real-world performance until extensive field validation is conducted.
3. **Geographic Scope:** The system's focus on Sri Lankan contexts may limit generalizability to other tropical agricultural regions without adaptation.

6. Future Works

Future development should prioritize,

1. **Real-World Data Integration:** - Collection and integration of actual greenhouse operational data to improve model generalization and validation.
2. **Advanced Regularization:** - Implementation of sophisticated regularization techniques to address overfitting in yield and growth prediction models.
3. **Sensor Integration:** - Development of IoT sensor capabilities for automated data collection while maintaining manual entry options.
4. **Cross-Cultural Adaptation:** - Research into system adaptation for different cultural contexts and geographic regions.
5. **Longitudinal Impact Assessment:** - Long-term studies tracking system impact on farmer outcomes across multiple growing seasons.
6. **Computer Vision Integration:** - Implementation of image-based pest detection using convolutional neural networks.

7. Conclusion

This research successfully developed an integrated machine learning-based Decision Support System for greenhouse crop management under mite infestation conditions. The system demonstrates proof-of-concept functionality combining synthetic data generation, ensemble machine learning models, and culturally appropriate interfaces for Sri Lankan agricultural contexts.

Key achievements include,

- Successful mite infestation prediction (86% accuracy), providing reliable early warning capabilities.
- Innovative synthetic data generation approach addressing fundamental data scarcity challenges.
- Functional system integration from data entry to actionable recommendations.
- Mobile-compatible interface design addressing technological constraints in developing regions.

The synthetic data generation approach using NetLogo simulation provides a replicable methodology for addressing data scarcity challenges in agricultural technology development. While model overfitting issues require further refinement, the research establishes a foundation for continued development and eventual field deployment.

The system's emphasis on accessibility and cultural appropriateness provides a model for agricultural technology development in developing regions, demonstrating that advanced computational techniques can be effectively adapted to serve farming communities with varying technological capabilities and infrastructure limitations. The integrated architecture serves as a platform for future agricultural research and demonstrates potential for transforming greenhouse management practices from reactive to predictive approaches.

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