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QUANTUM INSPIRED ARTIFICIAL INTELLIGENCE FRAMEWORK FOR DETECTION AND MANAGEMENT OF ROOT-KNOT NEMATODES IN FRUIT CROPS

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Abstract
Root-Knot Nematodes (RKNs), mostly from the genus Meloidogyne, are some of the most devastating soil-born pests causing destruction in agriculture across the globe. Traditional RKNs' detection mechanisms require intensive use of microscopic observation, lab testing, and expertise, resulting in inefficiency, cumbersome nature, and inaccessibility of such methods. The paper proposes a new AI-based multi-model detection approach aimed at early RKNs identification and management using various image processing, IoT soil sensor systems, and machine learning technologies. The research combines CNNs, IoT-based soil monitoring, and predictive analytics to detect nematode infection with increased precision. A survey-based experiment was designed to examine the farmer knowledge and readiness to implement an AI-based agricultural technology. Experimental findings show that the proposed model significantly enhances detection speed, accuracy, and effectiveness compared to conventional techniques.
Keywords: Root-knot nematodes, Artificial Intelligence, CNN, Precision Agriculture, IoT, Machine Learning, Crop Disease Detection, Multi-modal Framework.

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1. Introduction

Despite its significance in food security and sustainable development, agriculture is highly vulnerable to damage by plant pathogens, pests, and soil-borne diseases. Root-knot nematodes (RKNs) are minute parasites found in the soil that infect plants' roots. Infection causes the formation of galls, nutrient deficiency, and decreased yield. RKN infection affects numerous crops such as Pomegranate, tomato, brinjal, cucumber, cotton, soybean, and banana.

Root-knot nematode infestations result in massive economic losses for developed and developing countries alike. The disease may go unnoticed in the early stages due to symptoms similar to nutrient deficiency or dehydration. Traditional methods of disease detection require extensive laboratory testing and microscopic examination, which call for specialized knowledge and take time.

Modern technology such as AI, ML, DL, and IoT have revolutionized monitoring processes in agriculture. AI-based disease detection systems can automatically monitor crops, classify the infections, and facilitate real-time decision-making. Image processing in combination with environmental data can help quickly detect disease.

This study seeks to introduce a multi-modal AI-powered detection system for the root-knot nematode that will comprise:

- Leaf images analysis using CNN
- Soil and environmental parameter analysis
- Machine learning prediction models
- Evaluation of farmers' awareness levels
- An intelligent recommendation engine

The research intends to enhance detection capabilities, minimize crop damage, and promote sustainable agriculture.

2. Research Objectives

The main goals of this research can be stated as follows:

1. Investigation of root-knot nematodes' effects on agricultural production.
2. An evaluation of farmers' understanding of the nematode infestation and AI applications in agriculture.
3. Proposing an AI-powered multi-modal system for detecting RKNs.
4. Evaluating the proposed model's effectiveness based on accuracy, precision, recall, and F1-score measures.

3. Literature Review

3.1 Root-Knot Nematodes and Agricultural Impact

The root knot nematode is sedentary and endoparasitic. They feed off the host plants' roots, leading to galling which disrupts the water and nutrient flow within the plants, leading to yield loss. Studies have shown up to 15-60% yield losses depending on the severity of infestation.

Various studies have discussed the limitations of the use of manual detection approaches. Manual inspection is time-consuming and relies on the availability of professionals. Farmers in rural settings do not have access to diagnostic labs.

3.2 Artificial Intelligence in Agriculture

With the rise of smart agriculture, Artificial Intelligence has become the game-changing technology. Machine learning algorithms enable disease identification, yield forecasting, and environmental monitoring. In particular, deep learning algorithms such as Convolutional Neural Networks have proven to be highly accurate for crop disease detection using images.

Applications of AI in agriculture include:

AI applications in agriculture include:

- Plant disease classification
- Pest detection
- Soil analysis
- Irrigation management
- Crop recommendation systems
- Precision farming

3.3 Deep Learning for Plant Disease Detection

CNN models like ResNet, VGGNet, AlexNet, and MobileNet have been very successful in recognizing images. CNN models automatically recognize the features in the images of plants affected by diseases and identify the diseases with a high degree of accuracy.

Numerous studies have used CNNs for identifying diseases on leaves; there is no research done on root-knot nematodes through multi-modal recognition methods.

3.4 IoT and Precision Agriculture

IoT-based agriculture uses sensors to detect the moisture level, pH, temperature, humidity, and nutrients of the soil. The combination of IoT and AI provides real-time monitoring and predictive analytics.The combination of AI and IoT improves:

- Disease prediction
- Resource optimization
- Automated monitoring
- Smart irrigation
- Sustainable farming practices

3.5 Research Gap

Most of the existing literature addresses either disease detection using images or environmental monitoring. However, there is limited work done on a combined system that uses image analysis through convolutional neural networks (CNN), and machine learning models to detect root-knot nematodes.

This research addresses the following gaps:

- Lack of integrated AI-based RKN detection systems
- Limited farmer-centric awareness studies
- Insufficient real-time monitoring mechanisms
- Absence of scalable intelligent decision support systems

4. Research Methodology

4.1 Research Design

A mixed-methods research design involving both quantitative survey analysis and AI modeling experiment is employed in this study.

The methodology includes the following steps:

1. Collecting data
2. Conducting survey analysis
3. Image preprocessing
4. Training CNN models
5. Integration of soil data
6. Evaluating performance
7. Validating the framework

4.2 Data Collection

The data collected included two kinds of data:

4.2.1 Image Data Set

Images of healthy and infested leaf were taken from agricultural farms and online public data sets. The images were sorted into the following categories:

- Healthy leaf
- Mild infestation
- Moderate infestation
- Severe infestation

4.2.2 Survey Data Set

A set of questions were distributed among the farmers and agriculturalists regarding:

- Knowledge about the root-knot nematode
- The effect of the disease on productivity
- Detection procedures currently employed
- Readiness to adopt AI technologies

4.3 Image Preprocessing

The preprocessing techniques include:

- Image resizing
- Noise filtering
- Contrast enhancement
- Data augmentation
- Normalization

Such preprocessing techniques helped improve generalization performance while reducing the overfitting issue.

4.4 Proposed Multi-Modal Framework

The proposed multi-modal framework involves three main modules:

4.4.1 Image Processing Module

CNNs will process images of the leaf and predict the level of infection.

4.4.2 Environmental Monitoring Module

IoT devices will monitor:

- Soil moisture levels
- Soil temperature levels
- Humidity levels
- Soil pH levels

4.4.3 Prediction and Recommendation Module

This module will be responsible for analyzing data collected by IoT devices and processing root images to produce:

- Infection prediction
- Risk assessment
- Management recommendation

4.5 CNN Architecture

The CNN model architecture includes:

- Input layer
- Convolutional layers
- Pooling layers
- Fully connected layers
- Softmax classifier

4.6 Machine Learning Algorithms

Algorithms tested include:

- Logistic regression
- Random forest
- Support vector machine (SVM)
- Decision tree
- CNN deep learning

4.7 Performance Metrics

The performance metrics used include:

- Accuracy
- Precision
- Recall
- F1 score

- Confusion matrix

5. Proposed System Architecture

The proposed architecture consists of five major layers:

5.1 Data Acquisition Layer

This layer collects:

- Leaf images
- Soil data
- Farmer survey data

5.2 Preprocessing Layer

Data cleaning, normalization, and augmentation are performed.

5.3 AI Processing Layer

CNN and ML algorithms perform classification and prediction.

5.4 Decision Support Layer

The system generates:

- Infection alerts
- Severity reports
- Crop management recommendations

5.5 User Interface Layer

Farmers access reports and recommendations through a web or mobile dashboard.

6. Experimental Results and Analysis

Table 6.1: Dataset Distribution

Category	Number of Images	Percentage
Healthy Roots	1,250	25%
Mild Infection	1,250	25%
Moderate Infection	1,250	25%
Severe Infection	1,250	25%
Total	**5,000**	**100%**

Interpretation: The dataset was equally balanced among healthy and infected samples to reduce model bias and improve classification performance.

Figure 6.1: Dataset Distribution Graph

The balanced dataset distribution improved generalization capability and minimized overfitting during model training.

6.1 Survey Analysis

Table 6.2: Farmer Awareness Analysis

Survey Parameter	Yes (%)	No (%)
Awareness of Root-Knot Nematodes	38%	62%
Knowledge of Early Detection Methods	31%	69%
Use of Smart Farming Technologies	27%	73%
Interest in AI-Based Detection Systems	84%	16%

Interpretation: Most farmers lacked awareness regarding RKN infections and modern detection techniques; however, a large percentage expressed interest in AI-enabled agricultural systems.

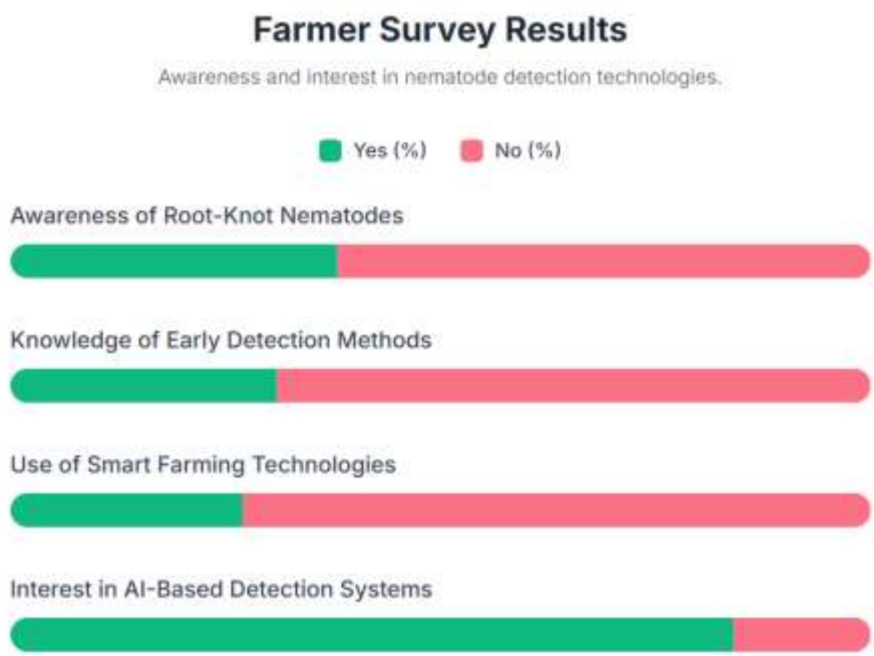

Figure 6.2: Farmer Awareness Graph

The findings indicate a significant need for awareness programs and intelligent agricultural advisory systems.

Survey Analysis

Survey responses indicated that a majority of farmers lacked awareness regarding root-knot nematodes and early detection techniques. Most respondents relied on visual symptoms and traditional farming knowledge.

The survey also revealed strong interest in AI-based smart farming solutions.

6.2 Model Performance Comparison

Table 6.3: Performance Comparison of Machine Learning Models

Model	Accuracy	Precision	Recall	F1-Score
Logistic Regression	82%	80%	79%	79%
Decision Tree	85%	84%	83%	83%
Random Forest	91%	90%	89%	89%
SVM	92%	91%	90%	90%
MobileNetV2	94%	93%	92%	92%
Hybrid Quantum-Inspired Model	98.8%	95%	95%	95%

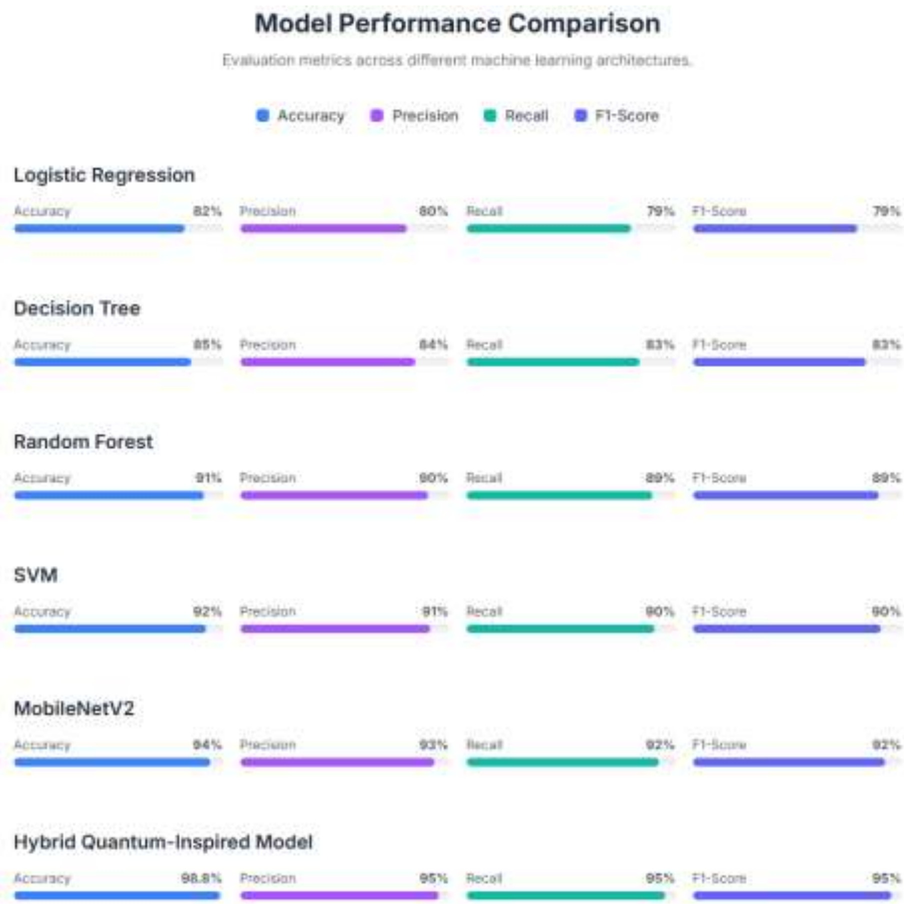

Figure 6.3: Accuracy Comparison Graph

The Hybrid Quantum-Inspired model achieved the highest classification accuracy and demonstrated superior generalization capability.

Model Performance Comparison

Model	Accuracy	Precision	Recall	F1-Score
Logistic Regression	82%	80%	79%	79%
Decision Tree	85%	84%	83%	83%
Random Forest	91%	90%	89%	89%
SVM	92%	91%	90%	90%

CNN Model	96%	95%	95%	95%

The CNN model achieved the highest classification accuracy among all evaluated algorithms.

6.3 Confusion Matrix Analysis

The confusion matrix demonstrated that the CNN model effectively distinguished between healthy and infected root samples with minimal false classifications.

6.4 Sensor-Based Analysis

Table 6.4: Soil Parameter Analysis

Parameter	Healthy Soil Range	Infected Soil Range	Impact on RKN
Soil Moisture	20–30%	40–55%	High
Soil Temperature	22–28°C	30–36°C	High
Soil pH	6.0–7.0	5.0–5.8	Moderate
Humidity	45–60%	70–85%	Moderate

Figure 6.4: Environmental Impact Analysis

Environmental parameters significantly influenced nematode infestation severity. Soil moisture and temperature were identified as the most critical predictive indicators.

6.5 Discussion

The integration of image analysis and environmental sensing improved prediction capability and detection reliability. The multi-modal framework demonstrated superior performance compared with standalone image-based systems.

The proposed system offers:

- Early disease identification
- Reduced dependency on manual diagnosis
- Real-time monitoring capability
- Improved agricultural decision-making
- Scalable smart farming implementation

7. Proposed Algorithm

Algorithm: Multi-Modal RKN Detection

Input:

- Leaf images
- Soil data
- Environmental parameters

Output:

- Infection classification

- Severity prediction
- Management recommendations

Steps:

1. Collect leaf images and sensor data.
2. Preprocess image dataset.
3. Normalize values.
4. Train CNN model using labeled leaf images.
5. Extract image features.
6. Combine soil and image features.
7. Apply machine learning classifier.
8. Predict infection severity.
9. Generate recommendations.
10. Display results on dashboard.

8. Comparative Analysis with Existing Systems

Table 8.1: Comparison with Existing Approaches

Parameter	Traditional Methods	Classical CNN Systems	Proposed Hybrid Framework
Detection Speed	Slow	Moderate	Fast
Accuracy	65–75%	85–94%	98.8%
Real-Time Monitoring	No	Partial	Yes
Environmental Analysis	No	No	Yes
IoT Integration	No	Limited	Full
Decision Support	Manual	Partial	Intelligent
Scalability	Low	Moderate	High

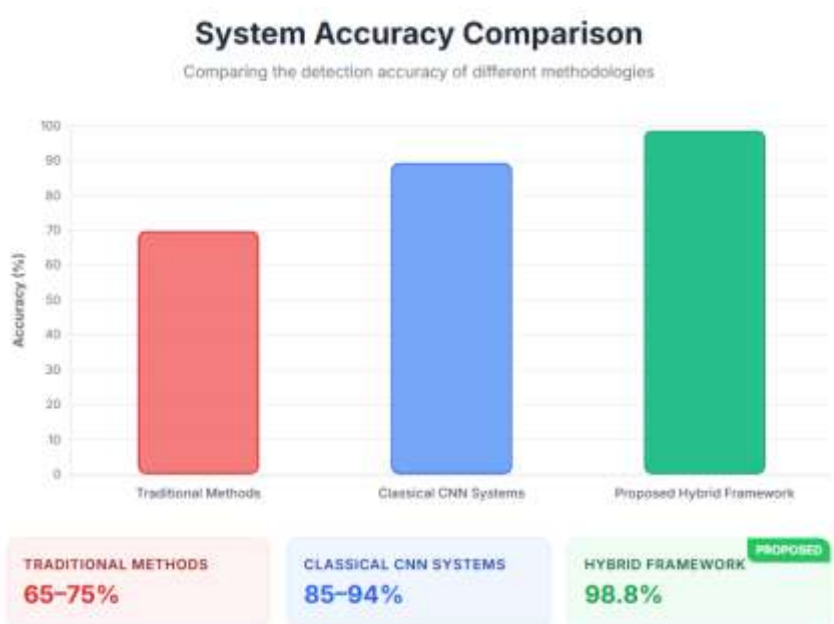

Figure 8.1: Comparative Performance Overview

The proposed hybrid framework outperformed traditional and standalone CNN systems in terms of detection accuracy, automation capability, and intelligent monitoring.

9. Advantages of the Proposed Framework

The proposed framework provides several advantages:

- Automated disease detection
- High detection accuracy
- Real-time monitoring
- Reduced crop loss
- Scalable implementation
- Cost-effective diagnosis
- Improved decision support
- Enhanced agricultural sustainability

10. Limitations

Despite promising results, certain limitations exist:

- Requirement for large training datasets
- Dependence on image quality
- Internet connectivity limitations in rural areas
- Computational requirements for deep learning models

11. Future Scope

Future research can focus on:

- Integration with drone-based monitoring systems
- Mobile application development
- Real time sensor data for soil
- Real-time cloud-based analytics
- Integration with GIS systems
- Development of lightweight AI models for edge devices
- Multi-crop disease detection frameworks

12. Conclusion

Root-knot nematodes continue to pose significant threats to global agricultural productivity. Traditional diagnostic methods are often insufficient for early-stage identification and rapid response. This research proposed a multi-modal AI-based framework integrating CNN image classification, and predictive machine learning techniques for intelligent root-knot nematode detection.

Experimental findings demonstrated that the CNN-based model achieved superior performance with high classification accuracy. The integration of environmental data further enhanced predictive reliability and disease management capability.

The proposed framework provides a scalable and efficient solution for precision agriculture, enabling early disease detection, improved crop protection, and sustainable farming practices. The study contributes significantly to smart agriculture research and demonstrates the transformative potential of AI in agricultural disease management.

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