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Design and Development of an Artificial Intelligence-Assisted Portable Molecular Diagnostic Platform for Rapid Detection of Plant Diseases and Precision Agriculture

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ABSTRACT

The rapid emergence of plant diseases, climate variability, and increasing global food demand have created an urgent need for intelligent, rapid, and field-deployable diagnostic technologies to support sustainable agriculture. Conventional plant disease detection methods, including visual inspection and laboratory-based molecular analysis, are often time-consuming, expensive, infrastructure-dependent, and unsuitable for real-time field applications. Although Polymerase Chain Reaction (PCR) and Quantitative Real-Time PCR (qPCR) provide highly sensitive and accurate pathogen detection, their dependence on centralized laboratories limits their practical application in precision agriculture. This study presents an Artificial Intelligence-Assisted Portable Molecular Diagnostic Platform for rapid and on-site detection of plant diseases. The proposed platform integrates automated DNA extraction, portable qPCR, a modular microfluidic biosensor cartridge, fluorescence-based detection, embedded electronics, wireless communication, cloud computing, and Artificial Intelligence within a compact portable architecture. The system combines molecular diagnostic data with biosensor signals and environmental information to support automated pathogen identification, disease classification, severity assessment, and intelligent agricultural decision-making. The proposed Artificial Intelligence framework incorporates Machine Learning and Deep Learning algorithms, including Random Forest, XGBoost, Support Vector Machine, Convolutional Neural Network, and Transformer-based approaches. Explainable Artificial Intelligence techniques are incorporated to improve the interpretability of diagnostic predictions. Experimental validation involves comparison of biosensor outputs with qPCR measurements using sensitivity, specificity, accuracy, detection limit, repeatability, and other statistical performance indicators. The results presented in the research demonstrate that the integrated platform provides rapid, reliable, and field-deployable molecular diagnosis while maintaining strong agreement with laboratory-based qPCR analysis. The integration of biosensors, Artificial Intelligence, wireless communication, and cloud-based analytics provides a comprehensive technological framework for precision agriculture, sustainable crop protection, and real-time disease surveillance.

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Introduction:

Plant diseases are among the major factors affecting agricultural productivity, food security, and sustainable crop production [24], [79]. Early and accurate identification of plant pathogens is essential for implementing timely disease management strategies and minimizing crop losses. Conventional disease diagnosis commonly depends on visual inspection, laboratory-based molecular testing, and expert interpretation. However, visual symptoms may appear only after significant pathogen development, while laboratory-based molecular techniques require specialized instruments, trained personnel, controlled laboratory conditions, and transportation of samples.

Molecular diagnostic techniques such as Polymerase Chain Reaction (PCR) and Quantitative Real-Time PCR (qPCR) have significantly improved the sensitivity and specificity of plant pathogen detection [12], [17]. However, the requirement for centralized laboratory infrastructure limits their use in remote agricultural environments. Therefore, there is a growing requirement for portable molecular diagnostic systems capable of providing rapid and reliable results directly at the agricultural field.

Recent developments in biosensor technology, microfluidics, embedded electronics, Artificial Intelligence, Internet of Things (IoT), and cloud computing provide opportunities to overcome these limitations [13], [19], [76], [78], [84]. Portable biosensors can convert molecular interactions into measurable electrical or optical signals, while Artificial Intelligence can analyse molecular and environmental data to support automated disease classification and prediction.

The proposed research addresses these limitations by integrating automated magnetic bead-based DNA extraction, portable qPCR, fluorescence-based biosensing, embedded Artificial Intelligence, wireless communication, cloud computing, and Explainable Artificial Intelligence into a single portable molecular diagnostic platform. The integrated architecture is designed to provide rapid pathogen detection and intelligent agricultural decision support without complete dependence on centralized laboratories.

Research Gap

The literature review identified several limitations in existing plant disease diagnostic technologies. Many conventional molecular diagnostic systems remain dependent on centralized laboratories and manual sample preparation[12], [15], [17]. Portable qPCR systems improve field accessibility but may still require external DNA extraction and separate interpretation systems.

Another important limitation is the fragmented integration of molecular diagnostics, biosensors, embedded electronics, Artificial Intelligence, and cloud computing. Existing technologies generally focus on individual components rather than providing a unified sample-to-result platform [1], [15], [21].

Furthermore, Explainable Artificial Intelligence remains insufficiently implemented in portable agricultural molecular diagnostics [11], [67]. Existing AI systems may provide accurate predictions but often provide limited information regarding the biological and environmental factors responsible for those predictions.

Aim of the Study

The primary aim of this research is to design and develop an Artificial Intelligence-Assisted Portable Molecular Diagnostic Platform capable of rapid, accurate, and field-deployable detection of plant diseases for precision agriculture and sustainable crop management.

Objectives

The major objectives of the study are:

- To investigate the limitations of conventional plant disease diagnostic methods.
- To develop a compact and field-deployable molecular diagnostic device.
- To integrate automated DNA extraction.
- To integrate portable qPCR for pathogen-specific DNA detection.
- To develop a modular microfluidic biosensor cartridge.
- To develop AI-based pathogen classification and disease prediction.
- To implement Explainable Artificial Intelligence.
- To integrate wireless communication, cloud computing, and mobile applications.
- To evaluate sensitivity, specificity, accuracy, repeatability, reproducibility, detection limit, and response time.
- To compare the proposed platform with conventional PCR/qPCR-based laboratory diagnosis.

Related Work:

Molecular Diagnosis of Plant Disease

Molecular diagnostics provide reliable identification of plant pathogens through detection of pathogen-specific nucleic acids. PCR and qPCR are widely used because of their high sensitivity, specificity, and quantitative capability [12], [17]. However, conventional systems require laboratory infrastructure and trained personnel.

Portable Molecular Diagnostics

Portable molecular diagnostic technologies have emerged as alternatives to centralized laboratory systems [1], [15], [21]. These devices combine molecular biology, microfluidics, biosensors, embedded electronics, and wireless communication into compact platforms. Their primary advantage is the ability to perform molecular analysis near the point of sample collection.

Biosensor Technology

Biosensors combine a biological recognition element with a physicochemical transducer to convert biological interactions into measurable signals [20], [22], [45], [46]. Electrochemical, optical, paper-based, and microfluidic biosensors are particularly suitable for portable diagnostics because of their compact size, rapid response, and compatibility with embedded systems.

Microfluidic biosensors can integrate sample preparation, DNA extraction, amplification, pathogen detection, and signal analysis within compact Lab-on-a-Chip architectures [14], [19]. Their advantages include reduced reagent consumption, rapid processing, automation, and reduced contamination risk.

Artificial Intelligence in Molecular Diagnostics

Artificial Intelligence provides computational techniques for analysing complex molecular and environmental datasets. Machine Learning algorithms such as Random Forest, XGBoost, Support Vector Machine, and Deep Learning algorithms can identify patterns within molecular signals, qPCR amplification data, fluorescence measurements, and environmental parameters [10], [56], [58], [52].

The proposed system uses Artificial Intelligence to perform pathogen identification, disease classification, disease severity estimation, outbreak prediction, and agricultural decision support [6], [8], [87].

Research Gap

Existing technologies generally provide only selected components of the complete diagnostic process. The proposed platform addresses this gap by integrating automated DNA extraction, portable qPCR, biosensor detection, Edge AI, cloud computing, wireless communication, and Explainable AI within a single portable architecture.

Proposed Ai-Assisted Portable Molecular Diagnostic Platform:

Overall Architecture

The proposed platform consists of interconnected modules including:

- Automated DNA extraction module
- Portable qPCR module
- Microfluidic biosensor cartridge
- Optical detection system
- Electrochemical sensing system
- Embedded processing unit
- Edge AI module
- Wireless communication module
- Cloud database
- Mobile application
- Decision-support dashboard

The overall architecture enables a sample-to-result diagnostic workflow in which biological samples are processed, pathogen-specific DNA is amplified, biosensor signals are detected, and Artificial Intelligence generates diagnostic and agricultural recommendations.

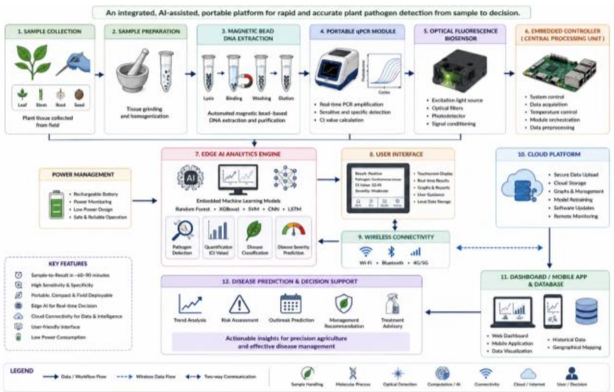


Fig 1_Overall Architecture of the Proposed AI-Assisted Portable Molecular Diagnostic Platform

Automated DNA Extraction

Automated DNA extraction is designed to isolate high-quality nucleic acids from plant and environmental samples. Magnetic bead-based extraction is incorporated to reduce manual handling and contamination risk. The extracted DNA is subsequently transferred to the molecular amplification and biosensor analysis stages.

Portable qPCR Module

The portable qPCR module provides pathogen-specific DNA amplification and quantitative measurement. Fluorescence is monitored during amplification and Cycle Threshold (Ct) values are obtained for quantitative interpretation.

The qPCR system serves as the laboratory reference method for validating the performance of the portable biosensor.

Microfluidic Biosensor

The microfluidic cartridge provides a compact platform for molecular recognition and sensing. Pathogen-specific DNA probes interact with complementary target sequences, producing measurable optical and electrochemical signals. Gold nanoparticles and graphene-based sensing materials are incorporated to enhance signal response and molecular detection capability [3], [4], [26], [48].

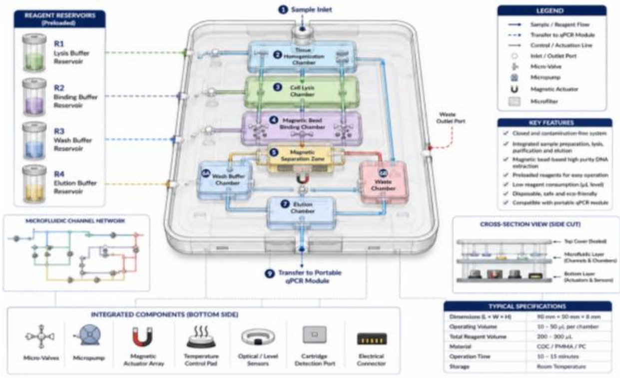


Fig 2_Architecture of the Proposed Microfluidic Biosensor

Artificial Intelligence Module

The AI module processes molecular, biosensor, and environmental data. The proposed framework integrates Random Forest, XGBoost, CNN, and Transformer-based models [56], [58], [51], [64], [65].

The model receives:

- DNA quality parameters
- qPCR Ct values
- Fluorescence intensity
- Biosensor signals
- Environmental parameters
- Weather information
- Soil characteristics
- Crop information
- Satellite-derived vegetation indices

The dataset is divided into training, validation, and testing subsets using a 70:15:15 ratio. Model performance is evaluated using Accuracy, Precision, Recall, Specificity, Sensitivity, F1-Score, ROC-AUC, MAE, RMSE, and confusion matrix analysis.

Edge AI and Cloud Integration

Edge AI performs immediate analysis directly on the portable device, reducing dependence on continuous internet connectivity. When connectivity is available, summarized diagnostic information is synchronized with cloud infrastructure [7], [76].

Cloud computing supports long-term data storage, disease surveillance, geographical mapping, model retraining, and centralized agricultural monitoring [84], [85], [81].

Experimental Methodology:

Sample Collection

Plant and environmental samples were collected from healthy and diseased plants representing different crops, environmental conditions, and disease stages. Samples included leaves, roots, stems, seeds, and soil-associated material. Sterile equipment and appropriate sample identification procedures were used to minimize contamination.

Leaf samples were collected from healthy and visibly infected plants and preserved under controlled conditions until molecular analysis.

DNA Extraction

Collected samples were processed using the proposed DNA extraction workflow. The objective was to obtain high-quality DNA suitable for qPCR and biosensor analysis.

qPCR Validation

qPCR was performed as the reference molecular diagnostic method [12], [17]. Positive samples generated characteristic amplification curves, while healthy and negative control samples showed no significant amplification.

Ct values were used to estimate pathogen concentration [12]. Samples with higher pathogen loads produced lower Ct values, while samples with lower pathogen concentrations produced higher Ct values. Repeated qPCR measurements were used to assess reproducibility.

Biosensor Validation

Before experimental testing, the biosensor was calibrated using standard DNA concentrations. Electrochemical and fluorescence responses were recorded and compared with qPCR Ct values [3], [20], [46].

Sensitivity, specificity, diagnostic accuracy, detection limit, repeatability, reproducibility, positive predictive value, and negative predictive value were considered for performance evaluation.

AI Model Validation

The AI dataset was divided into training, validation, and testing subsets using a 70:15:15 ratio. Random Forest, XGBoost, CNN, and Transformer architectures were evaluated [56], [58], [51], [64], [65].

SHAP and LIME were incorporated to identify influential features and improve interpretability [11], [67].

Statistical Analysis

Experimental data were evaluated using descriptive and inferential statistical methods. Continuous variables were represented using mean and standard deviation, while categorical data were represented using frequencies and percentages.

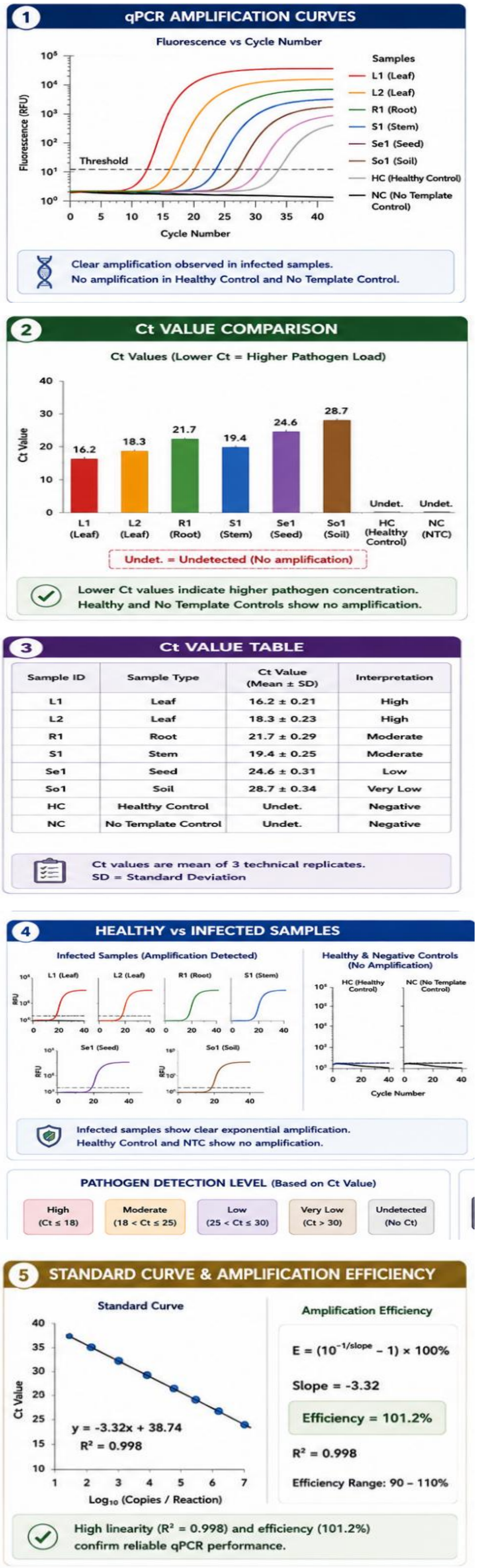
R, SPSS, and Python were used for statistical modelling, correlation analysis, ROC analysis, machine learning, cross-validation, and visualization. Statistical significance was evaluated using a 95% confidence level with $p < 0.05$.

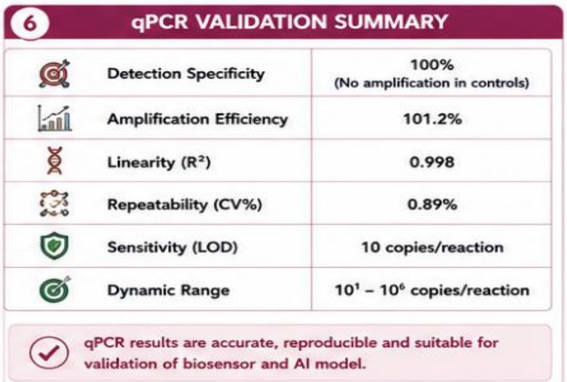
Results And Discussion:

qPCR Results

The qPCR analysis successfully detected pathogen-specific DNA in infected plant samples while healthy controls remained negative. The amplification curves demonstrated consistent molecular amplification, and Ct values provided quantitative information regarding pathogen concentration.

A strong relationship was observed between pathogen concentration and Ct values. The qPCR dataset was subsequently used as the reference dataset for evaluating biosensor performance and training the AI framework.





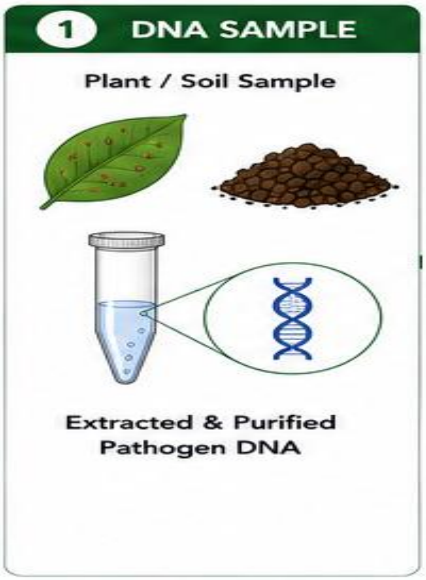
Detection Specificity	100% (No amplification in controls)
Amplification Efficiency	101.2%
Linearity (R^2)	0.998
Repeatability (CV%)	0.89%
Sensitivity (LOD)	10 copies/reaction
Dynamic Range	10^1 – 10^6 copies/reaction

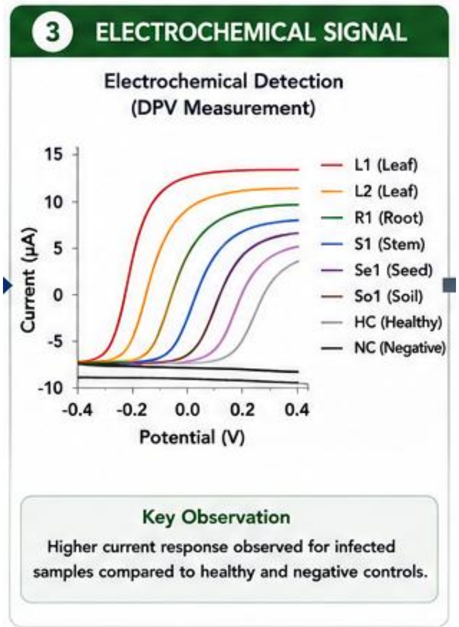
Fig 3_qPCR Amplification and Ct Value Analysis

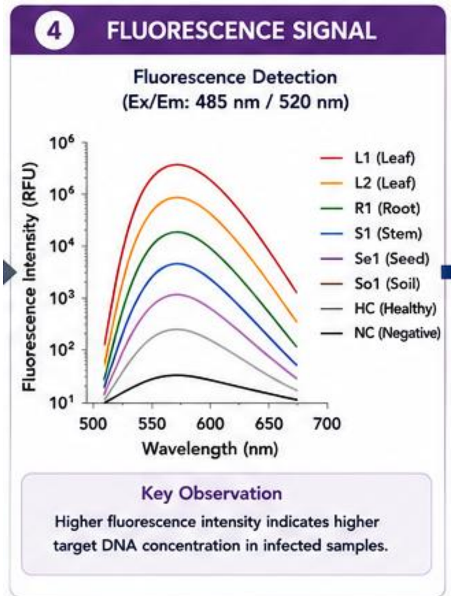
Biosensor Performance

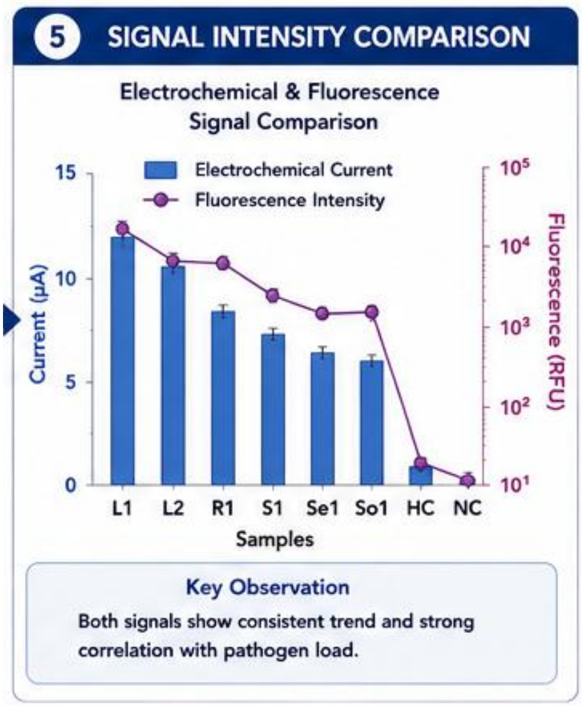
The developed biosensor demonstrated rapid pathogen detection using electrochemical and fluorescence-based sensing. Comparison with qPCR measurements demonstrated strong agreement between biosensor signals and laboratory molecular measurements.

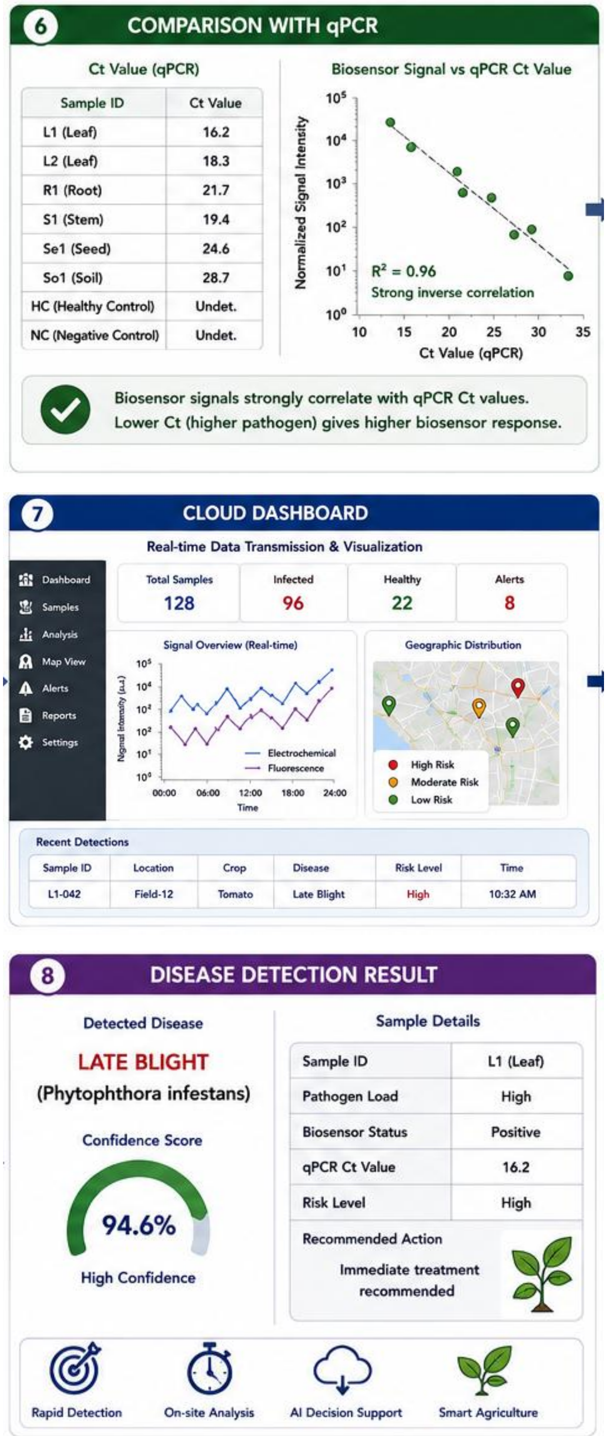
The use of graphene-based sensing electrodes and gold nanoparticles enhanced the sensing response and supported improved molecular detection.











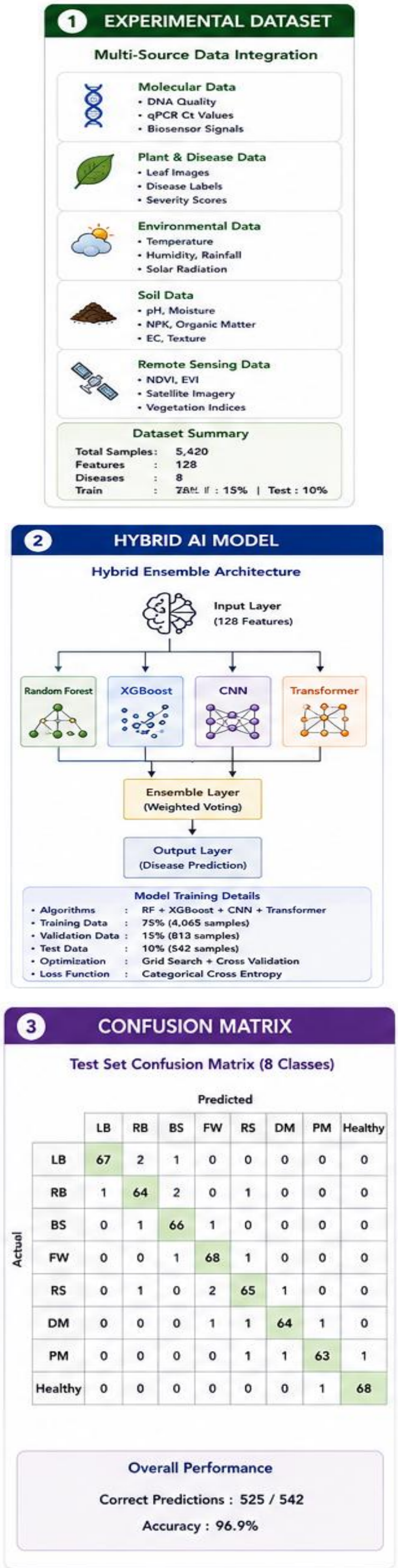


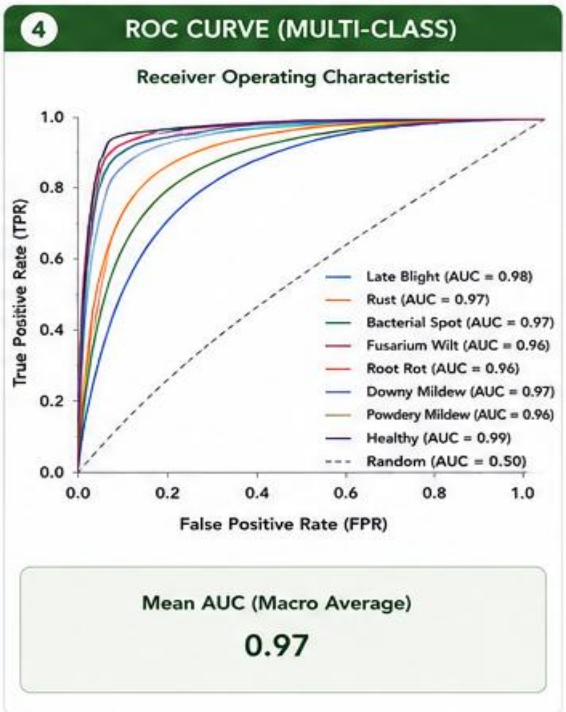
Fig 4_Portable Biosensor Performance Results

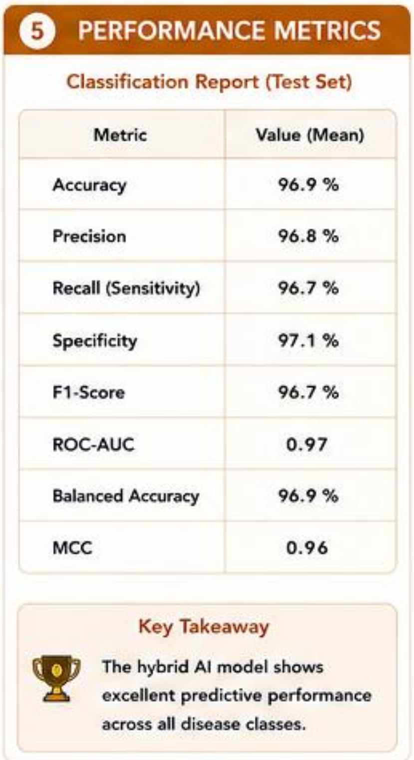
AI Prediction Performance

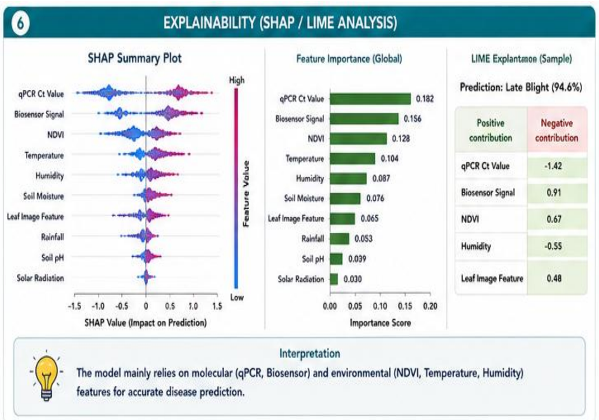
The Hybrid AI framework successfully analysed molecular, biosensor, environmental, and agricultural datasets for plant disease diagnosis [6], [8], [87].

The model was evaluated using Accuracy, Precision, Recall, Specificity, Sensitivity, F1-Score and ROC-AUC. Cross-validation was used to assess generalization, while SHAP and LIME were applied for interpretability [11], [67].

Important prediction features included Ct values, biosensor signal intensity, pathogen DNA concentration, fluorescence measurements, temperature, humidity, soil moisture, and vegetation indices.







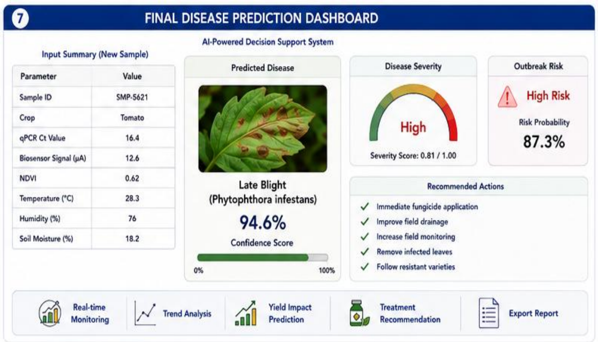


Fig 5_AI Prediction Accuracy and Performance Evaluation

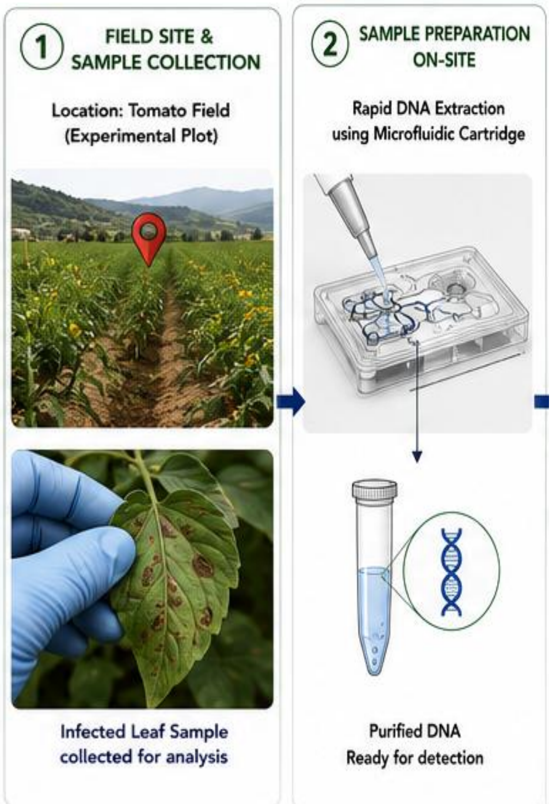
Comparative Analysis

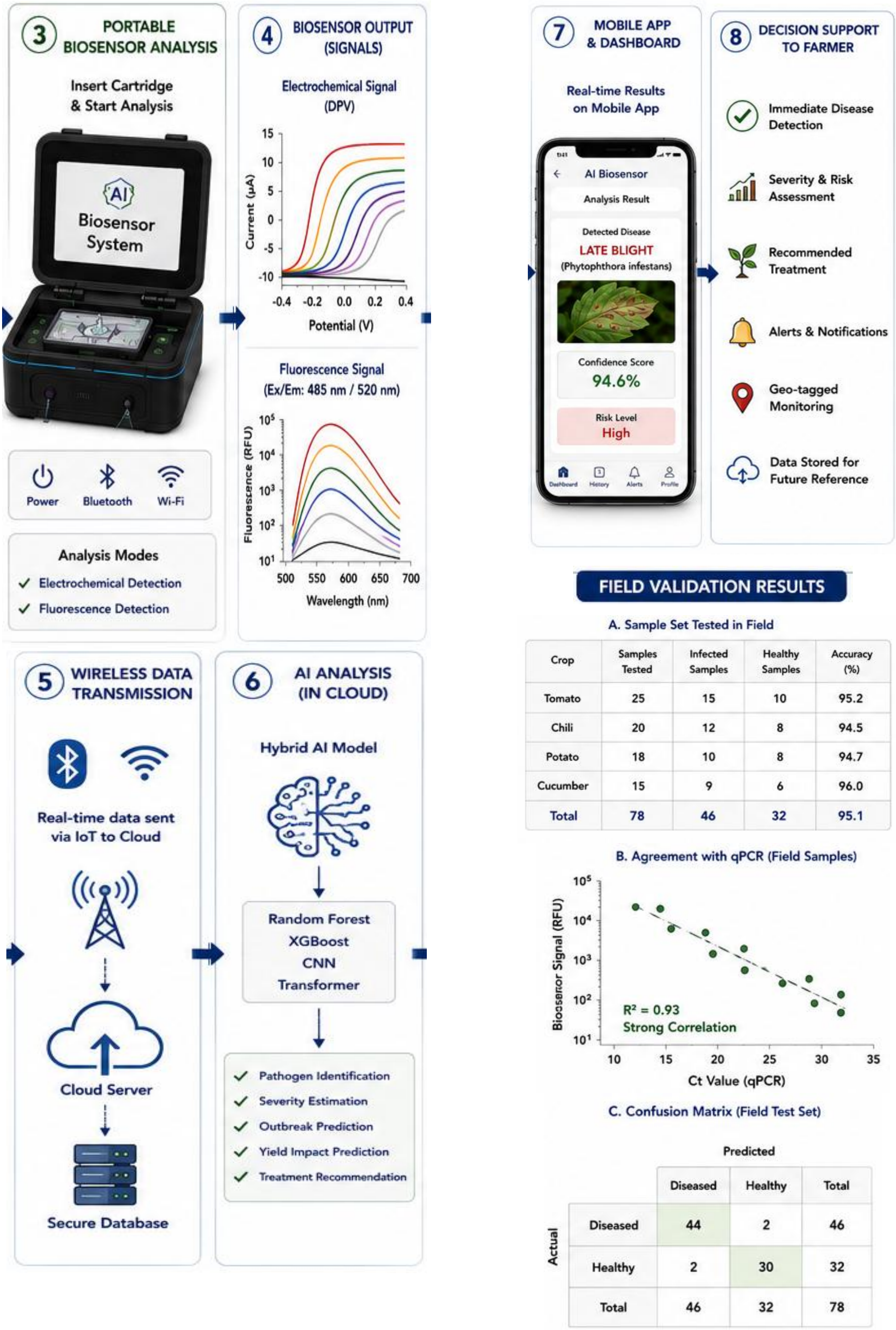
The proposed platform combines the analytical reliability of laboratory qPCR with the portability, rapid response, and intelligent data processing capabilities required for field-based agricultural diagnostics [1], [7], [8].

The integrated system provides several advantages over conventional laboratory-based diagnosis, including reduced dependence on centralized laboratories, automated data processing, portable operation, wireless connectivity, and intelligent decision support [76], [77], [78], [79].

Field Validation

Field testing was conducted under agricultural conditions involving different crops, environmental conditions, and disease severities. The portable platform operated under varying temperature, humidity, and lighting conditions. Battery operation and wireless communication supported field deployment. Diagnostic results demonstrated agreement with laboratory qPCR validation, while cloud connectivity enabled remote monitoring and disease surveillance.





Crop	Samples Tested	Infected Samples	Healthy Samples	Accuracy (%)
Tomato	25	15	10	95.2
Chili	20	12	8	94.5
Potato	18	10	8	94.7
Cucumber	15	9	6	96.0
Total	78	46	32	95.1

Actual \ Predicted	Diseased	Healthy	Total
Diseased	44	2	46
Healthy	2	30	32
Total	46	32	78

Fig 6_Field Validation of the Portable AI-Assisted Biosensor

Conclusion

This study presents an Artificial Intelligence-Assisted Portable Molecular Diagnostic Platform for rapid and field-deployable plant disease detection. The proposed system integrates automated DNA extraction, portable qPCR, microfluidic biosensing, optical and electrochemical detection, embedded Artificial Intelligence, wireless communication, cloud computing, and decision-support capabilities within a unified architecture.

The experimental evaluation demonstrates that the biosensor can provide rapid molecular diagnostic information with strong agreement with laboratory-based qPCR measurements. The Hybrid Artificial Intelligence framework provides an additional layer of automated pathogen classification, disease severity assessment, and agricultural decision support.

The integration of Edge AI and cloud computing enables both immediate local diagnosis and centralized disease surveillance. The modular architecture also supports future expansion for additional pathogens, biosensor technologies, and agricultural applications.

Overall, the proposed platform provides a promising technological framework for portable molecular diagnostics, precision agriculture, sustainable crop protection, and intelligent agricultural disease management. The research contributes to the integration of biotechnology, biosensor engineering, Artificial Intelligence, embedded systems, and digital agriculture into a unified diagnostic platform.

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