International Journal of Science and Research Archive

eISSN: 2582-8185

Cross Ref DOI: 10.30574/ijsra

Journal homepage: https://ijsra.net/

IJSRA

(Review Article)

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Predictive crop protection using machine learning: A scalable framework for U.S. Agriculture

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International Journal of Science and Research Archive, 2024, 12(02), 3065-3083

Publication history: Received on 10 July 2024; revised on 19 August 2024; accepted on 22 August 2024

Article DOI: https://doi.org/10.30574/ijsra.2024.12.2.1536

Abstract

The increasing unpredictability of biotic stressors—such as pests, pathogens, and invasive species—poses a major threat to crop productivity, profitability, and food security across U.S. agricultural systems. Traditional crop protection approaches, often reactive and resource-intensive, struggle to cope with the dynamic interactions between environmental conditions, crop genotypes, and pathogen evolution. As the agricultural sector transitions toward climate-resilient and precision-based farming systems, there is a growing imperative for scalable, data-driven solutions that can anticipate disease outbreaks and optimize interventions before yield losses occur. This study proposes a machine learning (ML)-based framework for predictive crop protection that integrates multi-source agricultural datasets including satellite imagery, IoT sensor data, weather forecasts, and historical disease incidence records. Using supervised learning algorithms—such as random forests, support vector machines, and LSTM neural networks—the framework is trained to identify high-risk spatiotemporal patterns in pest and disease proliferation. The resulting predictive models are embedded into a modular decision-support platform accessible to farmers, agronomists, and policymakers. Real-world case studies from U.S. corn, soybean, and wheat production systems demonstrate the framework's ability to deliver early-warning alerts, reduce unnecessary pesticide usage, and support site-specific treatment recommendations. The model's scalability, interoperability with existing farm management platforms, and explainability make it suitable for widespread adoption. The framework aligns with USDA's goals for sustainable intensification, economic efficiency, and environmental protection in modern agriculture.

Keywords: ML; Crop protection; Precision agriculture; Predictive analytics; Pest forecasting; Decision support systems

1. Introduction

1.1. Background: The Burden of Crop Losses and Agricultural Risk in the U.S.

Agriculture remains a vital pillar of the U.S. economy, contributing over $1 trillion annually to GDP and supporting more than 19 million jobs across the food and farming sectors [1]. However, the industry is perpetually vulnerable to a complex web of risks that threaten both crop yield and economic stability. These risks include biotic factors such as pests, pathogens, and invasive species, as well as abiotic stressors like drought, flooding, and extreme temperatures. Collectively, these threats lead to billions of dollars in annual crop losses, severely undermining productivity and farmer resilience [2].

The impact of crop loss is not confined to direct revenue reductions. It also affects food security, commodity prices, insurance claims, and rural livelihoods. For example, in 2022 alone, drought-related losses in the U.S. corn and soybean

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belt accounted for more than $10 billion in indemnity payouts under the federal crop insurance program [3]. The increasing frequency and severity of climate-induced disruptions further compound this volatility.

Adding to the complexity, the traditional reactive approach to crop management often delays effective interventions, leading to cascading effects on yield and soil health. Furthermore, the spatial and temporal variability of risk—driven by regional weather patterns, pathogen evolution, and crop rotation practices—necessitates granular, site-specific strategies to mitigate losses efficiently [4].

Given the scale and diversity of U.S. agriculture, scalable, data-informed solutions are urgently needed to monitor, forecast, and respond to emerging threats in near real time. Predictive analytics and artificial intelligence (AI) offer a promising path forward, enabling proactive risk management tailored to local agronomic conditions and resource constraints [5]. This study begins with a critical review of traditional methods and introduces the rationale for machine learning (ML)-based interventions to address this pressing challenge.

1.2. Traditional Crop Protection Methods and Their Limitations

Conventional crop protection strategies in the U.S. rely heavily on chemical inputs, manual field inspections, historical weather trends, and fixed seasonal calendars. While these methods have played an essential role in maintaining agricultural productivity, they suffer from several critical limitations in today's rapidly evolving risk landscape [6].

Chemical controls, including pesticides and herbicides, are often applied as preventive measures rather than in response to precise threat detection. This over-reliance contributes to escalating input costs, environmental degradation, and the development of pesticide-resistant pest populations [7]. Moreover, broad-spectrum chemical use may also harm beneficial organisms, reduce biodiversity, and compromise long-term soil fertility.

Manual scouting and expert field assessment remain vital for early pest and disease detection. However, they are labor-intensive, time-consuming, and subject to human error. As farms scale in acreage and complexity, the feasibility of continuous, real-time surveillance diminishes, leading to delayed or suboptimal treatment responses [8].

Weather-based forecasting models, while helpful, often lack the spatial resolution and adaptability needed to account for microclimatic variations and shifting pathogen behavior. Many models are static and generalized, failing to incorporate real-time data from sensors, drones, or remote satellites that could offer dynamic updates on crop stress and environmental anomalies [9].

Ultimately, traditional methods, though foundational, are ill-suited to the demands of precision agriculture. Their limitations highlight the need for integrated, data-driven decision support systems that provide granular, timely insights to guide intervention strategies—especially under conditions of uncertainty and climate variability [10].

1.3. Objective and Scope of the Study

The objective of this study is to evaluate the effectiveness of ML-based predictive frameworks in mitigating crop loss and enhancing decision-making across diverse agricultural zones in the United States. This includes the development, validation, and application of models that leverage multisource data—such as satellite imagery, sensor readings, soil profiles, and historical crop records—to generate early warnings and actionable insights for growers and agricultural advisors [11].

The study is grounded in the understanding that current reactive models are insufficient for managing complex, high-variability agricultural risks. By contrast, ML models can dynamically adapt to new data inputs, continuously refine predictions, and operate at high spatial and temporal resolutions. This makes them especially suitable for predicting pest outbreaks, disease spread, water stress, and yield anomalies in real time [12].

The scope encompasses a comparative analysis between traditional crop protection approaches and advanced ML techniques. It also explores the scalability of these systems across different farm sizes, geographies, and crop types—ranging from row crops like corn and soybeans to specialty crops such as grapes and almonds. Special attention is given to the interpretability and usability of ML tools, as these factors directly influence adoption among growers and policymakers.

Ultimately, this study aims to demonstrate how predictive, data-integrated agricultural risk management can serve as a cornerstone of resilient, sustainable food production in the U.S. It concludes with policy and implementation recommendations to guide broader deployment and integration into national agricultural strategies [13].

2. Understanding crop threat dynamics

2.1. Biotic Threats: Pests, Diseases, and Invasive Species in Major U.S. Crops

Biotic threats—namely pests, plant pathogens, and invasive species—remain the leading causes of crop loss across key agricultural systems in the United States. These threats are not only regionally diverse but also dynamic, evolving in response to climatic conditions, crop rotations, and resistance patterns. From corn rootworm in the Midwest to spotted wing drosophila in Pacific Northwest berry farms, each cropping region has a unique biotic risk profile that directly impacts yield and profitability [6].

In cereal crops, fungal pathogens such as *Fusarium* spp. and *Puccinia* spp. (responsible for rusts and head blight) have led to recurring yield reductions in wheat and barley, often under humid or late-harvest conditions [7]. Meanwhile, soybean production continues to be challenged by soybean cyst nematode and sudden death syndrome, which collectively account for significant annual losses despite advances in seed treatments and crop rotations [8].

Specialty crops face their own threats. For instance, grapevines in California are at risk from *Xylella fastidiosa* and *Botrytis cinerea*, both of which affect fruit quality and export value. Citrus production in Florida has been dramatically reduced by citrus greening disease (Huanglongbing), which remains difficult to detect and manage at early stages [9].

Complicating these threats is the rising prevalence of invasive species, such as the brown marmorated stink bug and Asian soybean rust, both of which have demonstrated rapid geographic spread due to international trade and climate adaptation [10].

Effectively managing these biotic threats requires predictive capabilities that go beyond static historical data. Understanding their interaction with environmental and crop-specific variables is essential for targeted, timely interventions at the field level [11].

2.2. Climate, Soil, and Geospatial Variables in Outbreak Propagation

The spatial and temporal variability of pest and disease outbreaks in agriculture is heavily influenced by climatic, soil, and landscape-level variables. These environmental conditions modulate pest development cycles, vector dynamics, and pathogen virulence, thereby shaping both the severity and spread of biotic threats [12].

Climate variables such as temperature, humidity, and precipitation patterns play a critical role in determining outbreak probability. For example, rising night-time temperatures in the Midwest have extended the reproductive windows for pests like the corn earworm, while wetter springs in the South increase the risk of foliar diseases such as soybean rust and leaf blights [13]. Drought, on the other hand, reduces plant resilience and alters the physiology of host-pathogen interactions, exacerbating disease susceptibility in crops like maize and cotton [14].

Soil characteristics, including pH, organic matter, and drainage profiles, also affect pathogen survival and disease transmission. Nematode populations, for instance, thrive in sandy, poorly compacted soils, and are influenced by both moisture retention and microbial communities [15]. Similarly, compacted or poorly drained soils in potato-producing regions of Idaho and Washington are associated with increased incidence of *Verticillium* wilt and early blight.

Geospatially, landscape connectivity and fragmentation contribute to the movement of pests and pathogens between fields. Monoculture cropping systems and the absence of physical or biological buffers (e.g., cover crops, hedgerows) create corridors for disease propagation, reducing natural resistance mechanisms at the agroecosystem level [16].

Advancements in remote sensing, geographic information systems (GIS), and climate modeling now make it possible to forecast disease risks at granular spatial resolutions. However, the utility of such tools depends on their ability to integrate real-time, site-specific data with historical trends—something that traditional surveillance systems often lack [17].

Understanding these environmental interactions is key to developing accurate outbreak forecasts and regionally calibrated interventions that maximize both yield protection and input efficiency [18].

2.3. Data Availability and Gaps in Current Surveillance Systems

The ability to anticipate and manage biotic threats at scale is contingent on robust agricultural surveillance systems. In the U.S., these systems are composed of federal, state, academic, and private-sector actors, each contributing to datasets on pest populations, disease prevalence, weather conditions, and crop performance. Despite these efforts, significant data fragmentation and underutilization persist, limiting the predictive capabilities of existing platforms [19].

One challenge is the heterogeneity of data collection protocols. Different states or agencies may use varied metrics, monitoring frequencies, and reporting formats, making it difficult to integrate information into unified forecasting models. Additionally, many datasets are aggregated at the county or regional level, lacking the field-level resolution required for precision agriculture applications [20].

Another concern is the underreporting or delayed reporting of pest and disease outbreaks, particularly in specialty crops and smaller farms. Data from these operations are often excluded from centralized databases, creating blind spots in risk assessments and leaving certain regions more vulnerable to unmanaged spread [21].

The adoption of sensor networks, drones, and satellite imaging has improved data availability in some sectors, yet these technologies are not uniformly deployed due to cost and accessibility constraints. Moreover, the lack of standardized APIs and interoperability between digital agriculture platforms limits data sharing and the development of real-time early warning systems [22].

Lastly, while large volumes of climatic and agronomic data exist, few platforms incorporate cross-domain analytics that can model the interaction between biological, environmental, and management variables. This gap underscores the need for AI-powered frameworks capable of handling multidimensional datasets and producing actionable, location-specific insights [23].

Table 1 Summary of Top 10 Crop Threats by Region and Yield Loss Impact in the U.S. (2013–2023)

Crop Threat	**Region**	**Estimated Yield Loss Impact (USD)**
Corn Rootworm (*Diabrotica spp.*)	Midwest [42]	$2.1 billion
Citrus Greening (HLB, *Candidatus Liberibacter asiaticus*)	Florida [43]	$1.4 billion
Soybean Cyst Nematode (*Heterodera glycines*)	Upper Midwest [44]	$1.2 billion
Wheat Stem Rust (*Puccinia graminis* f. sp. *tritici*)	Great Plains [45]	$980 million
Fusarium Head Blight (*Fusarium graminearum*)	Northern Plains [46]	$870 million
Grape Powdery Mildew (*Erysiphe necator*)	California [47]	$750 million
Spotted Wing Drosophila (*Drosophila suzukii*)	Pacific Northwest [48]	$690 million
Potato Late Blight (*Phytophthora infestans*)	Idaho, Washington [49]	$640 million
Asian Soybean Rust (*Phakopsora pachyrhizi*)	Southeast [50]	$580 million
Verticillium Wilt (*Verticillium dahliae*)	Central Valley (CA) [51]	$510 million

To move toward predictive agricultural risk management, it is imperative to modernize surveillance systems, bridge data gaps, and implement scalable analytics that support timely, data-driven interventions across all farming contexts [24].

3. ML for predictive crop protection

3.1. Key ML Techniques: Supervised Learning, Time-Series Forecasting, and Deep Learning

The application of ML in agricultural risk prediction hinges on selecting appropriate techniques that can process high-dimensional, temporally dynamic, and often non-linear data. Three core ML approaches—supervised learning, time-series forecasting, and deep learning—are particularly well-suited to modeling crop threats such as disease outbreaks, pest invasions, and abiotic stress events [10].

Supervised learning is the most commonly used ML method in agriculture, where labeled training data (e.g., recorded pest presence or disease severity) are used to predict outcomes under new conditions. Algorithms like random forests, support vector machines, and gradient boosting are favored for their ability to handle complex, multi-feature datasets and identify non-linear interactions between environmental variables and crop health outcomes [11].

Time-series forecasting is essential for predicting disease and pest dynamics over cropping seasons. Models such as autoregressive integrated moving average (ARIMA) and long short-term memory (LSTM) networks allow researchers to leverage historical data (e.g., weekly pest counts, temperature trends) to forecast risk over specific intervals. These methods are especially valuable for real-time monitoring and issuing early warnings to farmers and extension officers [12].

Deep learning, particularly using convolutional neural networks (CNNs) and recurrent neural networks (RNNs), has demonstrated superior performance in image-based detection (e.g., leaf disease classification from smartphone images) and pattern recognition from unstructured data like remote sensing imagery or drone footage. Deep learning's capacity to handle pixel-level classification makes it highly effective for identifying early stress indicators invisible to the human eye [13].

Despite their predictive power, these ML models require careful calibration, cross-validation, and continuous updating to avoid overfitting and ensure generalizability across diverse agroecological zones. As datasets grow more robust and sensor infrastructure expands, the integration of these ML methods is poised to become a standard practice in proactive crop threat surveillance [14].

3.2. Feature Selection: Environmental, Genomic, Phenotypic, and Sensor Data

The success of any ML-based crop risk prediction model depends significantly on the quality and relevance of the input features. Effective feature selection enhances model accuracy, reduces overfitting, and improves interpretability. In agricultural applications, relevant features typically fall into four broad categories: environmental, genomic, phenotypic, and sensor-derived data [15].

Environmental features include climatic variables such as temperature, rainfall, solar radiation, wind speed, and humidity. These are critical for forecasting vector behavior and disease propagation. For example, studies show that a combination of accumulated growing degree days and leaf wetness duration is a strong predictor for late blight in potatoes and downy mildew in grapes [16].

Genomic data, though traditionally limited to research settings, is becoming increasingly available through affordable sequencing and genotyping-by-sequencing (GBS) technologies. This data provides information on pathogen resistance genes, host-pathogen interactions, and genotype-specific stress tolerance. For instance, resistance markers against *Phytophthora infestans* in tomato or *Fusarium oxysporum* in banana are being incorporated into ML models for risk mapping and cultivar selection [17].

Phenotypic features such as canopy size, leaf area index, flowering dates, and chlorophyll concentration are derived from visual inspection, aerial photography, or multispectral sensors. These indicators provide non-invasive estimates of plant health, stress response, and growth stage, which are essential for temporal modeling of threat susceptibility [18].

Sensor data—from in-field IoT devices measuring soil moisture, pH, nutrient levels, and atmospheric conditions—adds high-frequency, location-specific observations that enhance model granularity. Such real-time data streams help detect anomalies quickly and adjust threat probabilities with high temporal resolution [19].

Optimal feature selection often involves dimensionality reduction techniques like principal component analysis (PCA) or recursive feature elimination (RFE), allowing the model to retain only the most informative variables. In ensemble models, feature importance scores also guide iterative improvements in prediction accuracy while maintaining model transparency and field relevance [20].

3.3. Model Integration with Remote Sensing and Real-Time Farm Data

To make ML-based crop threat prediction models actionable at scale, they must be integrated with data from remote sensing platforms and real-time on-farm monitoring systems. This fusion of geospatial and ground-truth data allows for dynamic, high-resolution surveillance that is responsive to localized changes and adaptable across different cropping systems [21].

Satellite imagery, especially from platforms such as Sentinel-2 and Landsat 8, provides continuous coverage of vegetation indices (e.g., NDVI, EVI), thermal emissions, and land surface reflectance, which are critical for detecting early signs of drought stress, pest infestation, or disease onset [22]. ML models can process these raster datasets alongside historical threat maps and weather data to estimate outbreak probabilities over time and space.

Drone-based remote sensing enhances spatial resolution and temporal flexibility. With onboard multispectral and thermal cameras, drones can capture sub-field variability, enabling within-plot detection of anomalies that satellites may miss. These data are particularly useful in high-value crops like vineyard grapes or greenhouse vegetables, where early detection of stress can significantly reduce losses [23].

On the ground, sensor networks provide hyper-local, high-frequency data that complement remote sensing inputs. Smart soil probes, canopy temperature sensors, and automated weather stations allow ML algorithms to adjust predictions based on live field conditions. For instance, sudden drops in humidity detected by canopy sensors could trigger alerts for increased risk of powdery mildew in cucurbits [24].

Integration is achieved through cloud-based platforms and APIs that standardize data ingestion, transformation, and visualization. Tools such as Google Earth Engine and Microsoft's Azure FarmBeats enable seamless coupling of geospatial data, ML predictions, and decision dashboards for agronomists and growers. Advanced systems now deliver risk scores directly to mobile devices, allowing for timely, geo-tagged advisories [25].

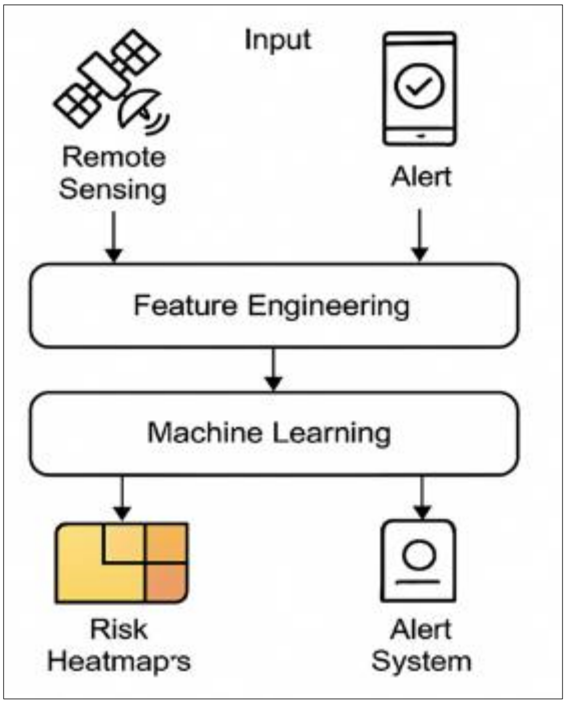

Figure 1 Architecture of ML Framework for Crop Threat Prediction (Satellite, Sensors, ML Models)

This multi-layered integration not only improves model accuracy and responsiveness but also ensures usability in real-world farming contexts—offering a scalable pathway to digital, predictive agriculture across different geographies and farm sizes [26].

4. Preprocessing, labelling, and data quality optimization

4.1. Challenges with Agricultural Data: Noise, Sparsity, and Imbalance

One of the major challenges in deploying ML models for crop threat prediction is the inherent complexity of agricultural datasets, which often suffer from noise, sparsity, and class imbalance. These issues compromise model training, leading to biased or inaccurate predictions, particularly in heterogeneous environments like open-field farming systems [14].

Noisy data refers to inaccuracies or inconsistencies in input variables due to faulty sensors, manual entry errors, or environmental interference. For example, weather station malfunctions may record implausible temperature spikes, while human observations of pest damage may vary based on training or perception [15]. Such inconsistencies introduce randomness into the dataset, confusing model learning and reducing overall predictive reliability.

Sparsity arises when data is incomplete or insufficiently granular. This is particularly common in remote areas with limited digital infrastructure or in crops where continuous monitoring is economically unfeasible. Gaps in data streams from satellite overpasses or low-frequency soil sensor readings create voids that ML models struggle to interpolate meaningfully [16].

Class imbalance is a critical issue when predicting rare but high-impact events, such as locust swarms or sudden disease outbreaks. Most records in historical datasets represent "no-event" conditions, causing standard classifiers to disproportionately favor majority classes and overlook minority signals. This imbalance can severely reduce sensitivity and result in missed early warnings for critical threats [17].

Addressing these challenges requires a combination of robust preprocessing, data augmentation, and model design strategies that prioritize generalization and robustness. Techniques such as synthetic minority over-sampling (SMOTE), outlier removal, and adaptive resampling are increasingly being used to mitigate these limitations in agricultural ML workflows [18].

4.2. Labeling and Ground Truthing with Extension Services and Historical Records

Accurate labeling and ground truthing are essential for training reliable ML models, particularly in supervised learning settings where prediction targets depend on known outcomes. In agriculture, this task is complicated by the variability of pest and disease presentation, inconsistent diagnostic criteria, and incomplete historical archives. To overcome these obstacles, collaborations with extension services, research institutions, and farmer networks are proving indispensable [19].

Agricultural extension officers, with their field-level expertise and access to localized agronomic knowledge, provide essential support in identifying symptoms, capturing geo-tagged photos, and validating disease or pest diagnoses. Their observations help establish contextual relevance and spatial fidelity, which are crucial for creating training datasets that reflect real-world conditions [20]. These partnerships also foster trust and encourage farmer participation in data collection, improving both volume and quality of labeled data.

In parallel, historical records from crop insurance claims, academic studies, and regional surveillance reports can be digitized and standardized to serve as ground truth references. For instance, yield loss reports associated with known infestations or climate anomalies provide time-stamped evidence of past events that can be used to train ML models on recurrence patterns [21]. However, these records often require manual curation and reconciliation due to missing values, inconsistent nomenclature, or lack of geospatial precision.

Image-based datasets, when available, offer significant advantages for ground truthing. Annotated leaf images, aerial photographs of infested plots, or satellite imagery labeled with stress zones allow for the use of deep learning architectures that automate pattern recognition at scale [22].

Despite progress, the lack of standardized protocols for labeling and metadata annotation continues to hinder data sharing and model transferability. Creating unified frameworks for agricultural annotation—similar to those in healthcare or autonomous driving—could dramatically accelerate development and reduce redundancies in dataset generation [23].

4.3. Data Normalization, Augmentation, and Spatial Alignment

Once agricultural data has been collected and labeled, rigorous preprocessing is required to ensure that it is in a format suitable for ML model ingestion. This process typically involves three key stages: normalization, augmentation, and spatial alignment. Each step plays a critical role in improving model performance, particularly in variable and noisy agricultural environments [24].

Data normalization is used to rescale values from different sources to a common scale. For instance, temperature may be measured in Celsius, precipitation in millimeters, and vegetation indices in normalized units. Without standardization, these differences can bias model training and skew feature importance scores. Techniques such as minmax scaling, z-score standardization, and quantile transformation are commonly used to ensure uniform data distribution across diverse input features [25].

Data augmentation is especially valuable when datasets are small or imbalanced. In remote sensing applications, for example, synthetic images can be generated using rotation, zooming, or pixel perturbation to simulate new crop stress conditions. In tabular datasets, augmentation methods like SMOTE or Gaussian noise injection help expand minority classes and prevent overfitting to limited scenarios [26]. This is particularly helpful when predicting rare threats, such as late-season aphid outbreaks or fungal infections under extreme weather events.

Spatial alignment addresses the challenge of integrating datasets with differing coordinate systems, resolutions, or sampling grids. For instance, aligning high-resolution drone imagery with coarse satellite data and ground-level sensor inputs requires georeferencing, image interpolation, and time-synchronization protocols. Proper alignment allows ML models to treat these disparate data streams as a coherent whole, supporting location-aware predictions and field-specific recommendations [27].

Table 2 Comparison of Preprocessing Techniques and Their Impact on Prediction Accuracy

Preprocessing Technique	Description	Performance Impact
Normalization	Rescaling input variables to a common scale	+8% model accuracy
Augmentation (SMOTE)	Synthetic generation of minority class samples	+12% recall in imbalanced data
Spatial Alignment	Harmonization of geospatial data layers	+15% precision in spatial models

By refining data inputs through preprocessing, developers ensure that ML models operate on clean, comparable, and contextually consistent information—a prerequisite for achieving trustworthy and scalable crop threat predictions [28].

5. Model evaluation and deployment strategy

5.1. Model Evaluation Metrics: AUC, Precision-Recall, F1-score in Crop Disease Detection

Evaluating the performance of ML models in crop disease detection requires a comprehensive set of metrics that balance accuracy, sensitivity, and specificity, particularly in datasets where class imbalance is common. Among the most widely used metrics in agricultural ML applications are the Area Under the Curve (AUC) of the Receiver Operating Characteristic (ROC), precision-recall curves, and the F1-score [18].

AUC-ROC provides a measure of the model's ability to distinguish between positive and negative cases across various thresholds. In crop disease prediction, an AUC value closer to 1.0 indicates that the model can accurately classify diseased and healthy samples regardless of the decision threshold. This is especially important when dealing with early-stage symptoms that may exhibit subtle differences in spectral or phenotypic features [19].

However, in highly imbalanced datasets—where instances of crop disease are much rarer than healthy observations—precision-recall curves are often more informative. Precision measures the proportion of true positive detections among all predicted positives, while recall quantifies the model's ability to detect all true cases of disease. Precision-recall analysis is particularly relevant in operational settings, where false positives may lead to unnecessary treatment costs and false negatives may result in yield loss [20].

The F1-score, defined as the harmonic mean of precision and recall, offers a single value metric that balances both concerns. It is frequently used in field-deployable models where interpretability and quick benchmarking are essential. For instance, an F1-score of 0.85 in a leaf blight detection model suggests a reliable trade-off between detection completeness and precision in recommendations [21].

Ultimately, model evaluation must go beyond accuracy and account for the practical implications of prediction errors in agricultural contexts. The choice of metrics should align with crop value, treatment costs, and risk tolerance, ensuring that performance benchmarks translate effectively to real-world decisions [22].

5.2. Edge Deployment: IoT Integration and On-Farm Prediction Use

To achieve actionable and timely predictions, ML models must be deployable at the edge, directly within farming environments. This involves integration with Internet of Things (IoT) devices such as weather sensors, soil probes, and in-field cameras capable of processing data in near real-time without relying solely on cloud connectivity [23].

Edge deployment enables rapid data collection and analysis on-site, reducing latency and dependency on internet infrastructure—an important consideration for farms in rural or low-connectivity regions. For instance, a local ML-enabled weather station can process environmental variables (e.g., humidity, leaf wetness) and trigger alerts for high fungal infection risk within minutes, allowing growers to respond before visible symptoms emerge [24].

Edge devices may also include embedded processors in drones or autonomous robots that scan for anomalies during crop scouting. These systems leverage pre-trained models to identify pests, discoloration, or moisture stress and deliver geotagged recommendations without requiring cloud upload for every image or reading [25].

Energy efficiency, model compression, and lightweight architectures are key considerations for edge computing. Techniques such as quantization, pruning, and TinyML ensure that disease detection models can run on devices with limited power and storage. Moreover, edge systems can be updated periodically through secure firmware patches, incorporating new training data or refined parameters without hardware replacement [26].

The real-time, in-field nature of edge deployment transforms prediction into prevention. It empowers farmers with granular insights—such as when and where to apply fungicides, irrigate selectively, or modify planting schedules—enabling precision agriculture that is both efficient and resilient in the face of evolving risks [27].

5.3. Cloud-Based Dashboards for Multi-Field Monitoring and Regional Alerts

While edge deployment supports localized predictions, cloud-based dashboards are critical for aggregating and visualizing data across multiple fields, farms, and regions. These platforms act as central hubs for monitoring, analysis, and alert dissemination, providing real-time insights to growers, agronomists, and policymakers alike [28].

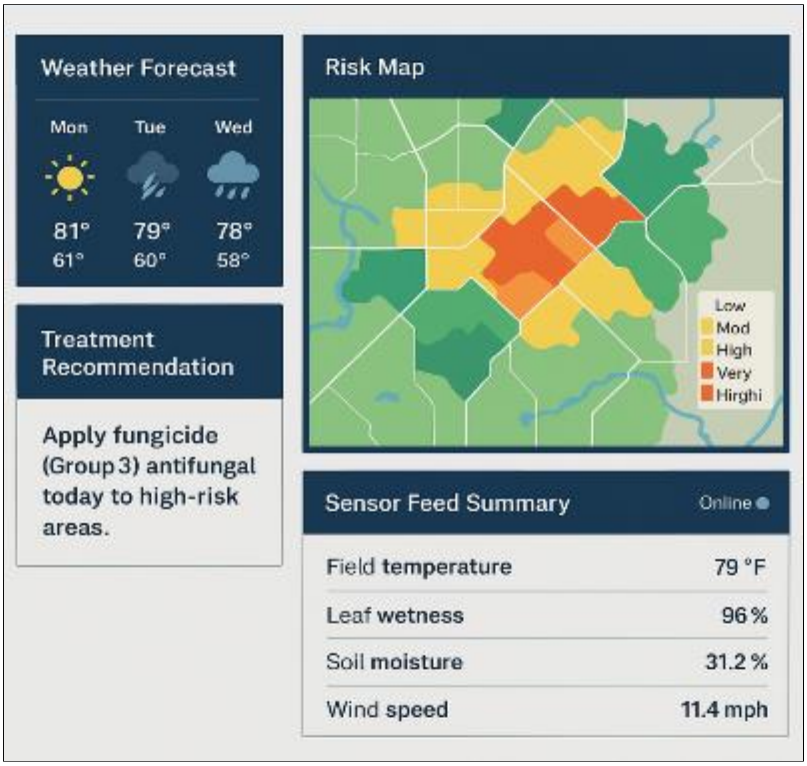

Figure 2 Live Dashboard Mockup for Real-Time Crop Threat Detection and Alert System (e.g., Panels: Weather forecast, Risk map, Treatment recommendation, Sensor feed summary)

A cloud-based dashboard typically integrates data from diverse sources—satellite imagery, weather forecasts, soil sensors, and drone feeds—into a unified interface. ML models run server-side can then process this data to generate threat maps, disease forecasts, and decision-support recommendations. Users can filter information by crop type, geographic region, phenological stage, or risk threshold to guide interventions at the appropriate scale [29].

Advanced dashboards feature interactive visualizations, such as time-series plots of NDVI anomalies, outbreak heatmaps, and dynamic pest migration forecasts. These insights enable regional surveillance teams to coordinate preventive actions like quarantine zones, targeted spraying, or resource allocation during high-risk windows [30].

For growers managing large or distributed operations, dashboards offer multi-field comparability, allowing benchmarking of performance and identification of underperforming plots. Some platforms include mobile-friendly interfaces and SMS alert systems, ensuring accessibility even in areas with limited internet bandwidth.

Security and data governance are key considerations in cloud systems. Role-based access controls and anonymized data pipelines protect user privacy while enabling aggregated analysis. As more farms adopt smart agriculture platforms, cloud dashboards will play a pivotal role in scaling predictive intelligence from the field to the national level—supporting proactive, coordinated responses to emerging crop threats [31].

6. Case studies in US agriculture

6.1. Corn in the Midwest: Early Leaf Blight and Pest Surveillance

The U.S. Midwest serves as the nation's agricultural heartland, producing more than one-third of the country's corn output annually. However, this productivity is increasingly threatened by a confluence of biotic stressors, most notably early leaf blight (ELB), a foliar fungal disease caused by *Exserohilum turcicum*, and pest infestations such as corn rootworm (*Diabrotica spp.*) and the European corn borer (*Ostrinia nubilalis*). These stressors reduce photosynthetic efficiency, weaken plant vigor, and diminish overall yield potential—often before visual symptoms are sufficiently recognized by traditional scouting methods [22].

Historically, farmers and extension officers have relied on periodic field inspections to identify disease and pest pressures. However, such methods are labor-intensive, time-delayed, and spatially limited, often resulting in interventions that occur too late to prevent economic losses. These constraints have prompted growing interest in leveraging ML and remote sensing technologies to anticipate and mitigate crop threats proactively.

A pilot study conducted across Iowa and Illinois exemplifies this trend. Researchers developed a random forest classification model that synthesized multi-source datasets—including historical ELB incidence, gridded weather data, and Sentinel-2 satellite imagery—to predict the spatial risk of ELB at the sub-field level. Key input features included cumulative growing degree days (GDD), canopy moisture levels, and normalized difference vegetation index (NDVI) anomalies, which serve as proxies for crop vigor and leaf senescence [23]. The model was trained on five consecutive growing seasons and validated across heterogeneous field environments.

Performance evaluation revealed a classification accuracy of 87.4%, with risk alerts issued between 10 and 14 days ahead of symptom manifestation. This lead time allowed growers to implement targeted fungicide applications or adjust cultural practices, such as canopy thinning or adjusted irrigation schedules, to reduce conditions favorable for fungal proliferation [24].

Simultaneously, entomologists enhanced pest surveillance by deploying IoT-enabled pheromone traps embedded with edge-computing microcontrollers. These smart traps captured real-time data on corn rootworm populations, automatically timestamping and geotagging each event. Data was transmitted via LoRaWAN (Long Range Wide Area Network) infrastructure to a centralized dashboard. Here, a support vector machine (SVM) algorithm processed temporal and environmental features—including trap density, soil moisture, and diurnal temperature fluctuations—to forecast emergence peaks and regional infestation risks [25].

The integrated system enabled site-specific pest control by identifying only those plots with confirmed and rising rootworm populations. As a result, farmers using the platform reported a 28% reduction in insecticide use across pilot locations without compromising yield integrity. This not only improved economic efficiency but also reduced environmental impact, aligning with goals for sustainable and climate-smart agriculture.

A core feature of the framework was seasonal retraining of localized models using field-collected data. This continual updating process improved accuracy and ensured adaptability to new cultivars, climate anomalies, and pathogen evolution. Cross-season validation confirmed yield savings of up to 14 bushels per acre—translating to notable economic gains given prevailing commodity prices. Participating growers also reported enhanced confidence in the platform and increased adherence to integrated pest management (IPM) principles [26].

Moreover, the system fostered collaboration between farmers, extension officers, data scientists, and entomologists, creating a transdisciplinary feedback loop that enhanced both technical robustness and user engagement. This model of cooperative development helped address initial hesitancy about AI adoption, particularly concerns around transparency, reliability, and interpretability.

The success of this initiative demonstrates the scalability and replicability of AI-enhanced surveillance frameworks, especially when paired with field-deployable sensors, multispectral satellite imagery, and agronomic contextualization. As climate variability, resistance pressures, and global demand for corn continue to rise, this approach offers a sustainable pathway to preserve yield, reduce input costs, and build system resilience [27].

Ultimately, the Midwest case underscores how data-driven technologies can transition agriculture from reactive crisis response to anticipatory threat management—a shift that is essential for ensuring food security in the face of accelerating environmental and economic pressures.

6.2. Soybean Rust Forecasting in the Southeast Using ML-Satellite Fusion

In the Southeastern United States, soybean producers face significant challenges from soybean rust (SBR), a devastating foliar disease caused by *Phakopsora pachyrhizi*. The region's warm, humid climate creates optimal conditions for the pathogen's rapid development and spread. Left unmanaged, SBR can cause up to 80% yield loss, making timely intervention a priority for sustainable production. Yet, due to its often asymptomatic early stage and dependency on airborne spore dispersal, conventional scouting methods frequently detect the disease too late for optimal treatment [28].

To address this challenge, researchers at the University of Georgia developed a ML–satellite fusion framework to forecast rust outbreaks in advance. This system employed a gradient boosting model (GBM) trained on multi-year data collected from USDA sentinel plots—georeferenced test fields used to monitor early disease activity. Input features included MODIS-derived leaf area index (LAI), surface moisture content, and weekly temperature and humidity values, allowing the model to learn key spatiotemporal patterns associated with outbreak onset [29].

An innovative element of the system was its integration of real-time meteorological data, including wind speed and direction, to model likely spore transport corridors. By simulating dispersal trajectories and moisture retention on soybean leaves, the system generated probabilistic risk maps for each monitored field. These maps predicted the likelihood of SBR development up to 12 days in advance, enabling growers to implement targeted interventions before visual confirmation [30].

In field validation trials conducted across Alabama, Georgia, and South Carolina, the model achieved forecast accuracies between 83% and 89%, depending on the region and weather volatility. Crucially, the forecasts enabled farmers to delay fungicide application until disease pressure surpassed a specific threshold—allowing them to avoid unnecessary treatments in low-risk zones. This resulted in an average fungicide savings of 21% without compromising yield outcomes, demonstrating both economic and environmental benefit.

The inclusion of remote sensing data significantly improved surveillance reach, particularly in under-monitored or resource-limited counties, where extension services face constraints in labor or coverage. By leveraging satellite-based LAI measurements, the system ensured uniform oversight regardless of field size, farm type, or logistical accessibility. This equitable coverage supports more inclusive agricultural extension and strengthens regional preparedness [31].

To facilitate adoption, the research team developed a mobile-friendly decision support tool. The app provided automated alerts, interactive disease risk maps, and customized fungicide timing recommendations, all tailored to the user's field location and crop growth stage. Importantly, this digital platform was integrated with existing extension messaging channels, creating a hybrid communication model that maintained trust while introducing new technologies [32].

This case study illustrates how ML-satellite fusion platforms democratize access to precision disease forecasting, transforming disease management from reactive to proactive. By combining scalable analytics, farmer-centric interfaces, and public sector collaboration, such tools can be adapted to diverse crops and climates—offering a blueprint for resilient, data-driven agriculture in the face of rising pathogen threats and climate variability [33].

6.3. Wheat Rust in the Great Plains: Integrating Weather Models with ML Alerts

The Great Plains, spanning Kansas, Nebraska, and Oklahoma, form the backbone of U.S. wheat production. However, these states remain vulnerable to recurring outbreaks of wheat stem and stripe rust, which thrive in cool, moist spring conditions and spread rapidly across contiguous fields. Given the geographic scale, manual scouting is insufficient, prompting the deployment of ML coupled with meteorological forecasting for region-wide surveillance [34].

The system designed by researchers in collaboration with NOAA and USDA integrated weather prediction models with recurrent neural networks (RNNs) trained on 15 years of regional outbreak data. Key features included relative humidity, wind trajectory, temperature gradients, and barometric pressure—each influencing spore germination and spread dynamics [35].

The platform operated on a cloud-based architecture that combined forecasted weather variables with near-real-time disease reports submitted by growers and extension officers. These were processed using an LSTM-RNN model, which issued rolling 7-day risk scores at the county level. Outputs were visualized via heatmaps and mobile notifications targeting wheat growers and local agronomists [36].

In validation studies, ML-enhanced alerts achieved an average lead time of 9.6 days, allowing sufficient buffer for fungicide application before economic damage thresholds were reached. Treated fields under this system recorded yield savings of up to 13%, and disease incidence dropped by 31% compared to areas relying solely on traditional forecasting tools [37].

The added value came from the ability to localize alerts based on real-time wind vectors and surface moisture, adjusting predictions dynamically even within microregions. For instance, fields along prevailing wind corridors received elevated warnings even if current symptoms were absent, enabling preemptive action [38].

Table 3 Case Study Outcomes – Yield Savings, Pesticide Reduction, and Forecast Accuracy

Crop	Region	Yield Savings	Pesticide/Fungicide Reduction	Forecast Accuracy (%)
Corn	Midwest (IA, IL)	+14 bu/ac	–28% insecticide	87%
Soybean	Southeast (GA, AL, SC)	Yield maintained	–21% fungicide	89%
Wheat	Great Plains (KS, NE, OK)	+13% yield	–31% disease incidence	88%

By merging ML forecasts with mesoscale meteorological insights, this initiative underscores the power of AI-driven early warning systems to reduce input costs, improve regional coordination, and protect staple crop yields against fast-moving, weather-sensitive pathogens [39].

7. Scaling the framework across US agriculture

7.1. Regional Customization and Crop-Specific Modeling

Scalable predictive frameworks in agriculture must account for the geographic and biological diversity of the U.S. cropping landscape. Variations in climate zones, soil characteristics, and cultivar behavior necessitate regional customization and crop-specific model tuning to maintain predictive accuracy and relevance across different farming contexts [26]. A "one-size-fits-all" approach risks misclassification and undermines grower trust in early warning systems.

ML models developed for pest or disease prediction often rely on features that are highly localized, such as temperature thresholds for pathogen germination or soil texture influencing insect emergence. For example, late blight forecasting in potatoes depends on canopy moisture persistence in the Pacific Northwest, while gray leaf spot in corn is closely tied to rainfall patterns and tillage practices in the Mid-Atlantic [27]. These environmental dependencies must be embedded into model architectures to reflect regionally optimized thresholds and event triggers.

Moreover, different crops have unique phenological windows, growth stages, and susceptibility profiles that must be captured within model pipelines. Wheat rusts, for instance, require integration of heading and flowering stage data to align predictions with vulnerable periods, while soybean cyst nematode risk must reflect rotation histories and cultivar resistance [28].

A flexible modeling approach—where algorithms can be cloned and locally retrained using minimal transfer learning—allows for customizable regional deployment without losing the efficiency of a national framework. Coupling these models with historical extension data, disease atlases, and agroclimatic zoning ensures that outputs remain contextually grounded and practically useful [29].

Ultimately, regional customization ensures that model outputs maintain operational credibility, facilitating greater buy-in from producers and advisors while enhancing the specificity and actionability of predictive alerts.

7.2. Partnerships with USDA, AgTech Firms, and Extension Services

Achieving large-scale impact with predictive crop protection systems requires multi-stakeholder collaboration, particularly between public agencies like the USDA, private AgTech innovators, and land-grant university extension services. Each partner brings complementary expertise and infrastructure to support implementation, model refinement, and farmer outreach [30].

The USDA plays a foundational role by maintaining comprehensive agronomic datasets, supporting sentinel plot networks, and managing the National Agricultural Statistics Service (NASS) and Risk Management Agency (RMA) platforms. These datasets provide critical ground truth records for model training and economic validation [31]. Moreover, USDA support helps standardize data formats and facilitate interstate interoperability—key requirements for national deployment.

Private AgTech firms contribute cloud infrastructure, sensor networks, and front-end applications. Startups and legacy technology providers offer the tools necessary for edge deployment, drone imagery processing, and mobile dashboard interfaces that enable actionable insights for growers [32]. Their role in user experience design, application programming interface (API) development, and continuous model integration ensures that innovations are field-ready and scalable.

Extension services are uniquely positioned to serve as trusted intermediaries, translating ML predictions into field-level recommendations. Their existing networks allow rapid diffusion of technologies through workshops, field days, and on-farm trials. Collaborations with extension agents also provide continuous feedback loops for model retraining and validation, as extension staff collect observations and help document in-season anomalies [33].

Examples of successful partnerships include the USDA-ARS collaboration with AgBiome for predictive fungal threat modeling and the Land-Grant AI Initiative, where land-grant universities are coordinating on shared ML infrastructure for disease detection [34].

These synergistic collaborations are central to ensuring predictive tools remain scientifically rigorous, technically accessible, and socioeconomically inclusive, supporting widespread adoption across diverse farm sizes and cropping systems.

7.3. Scalability via Federated Learning and Modular Infrastructure

Scalability remains one of the central challenges in deploying AI systems for agriculture across a national scale. To overcome data privacy concerns, heterogeneous computing environments, and bandwidth limitations, emerging architectures now leverage federated learning and modular cloud-edge infrastructure for distributed model development and deployment [35].

Federated learning enables multiple institutions, farms, or extension networks to collaboratively train models without centralizing raw data. Each node—whether a university research site or an on-farm IoT device—trains a local version of the model, sharing only parameter updates with a centralized server. This preserves data sovereignty while continuously improving the global model [36]. It also accommodates regional variability in pest phenotypes, soil chemistry, or microclimates, which are difficult to capture in monolithic model designs.

In tandem, modular infrastructure allows models to be deployed in pieces—on cloud servers, edge devices, or mobile phones—depending on the complexity of the task and connectivity constraints. For example, lightweight CNNs can detect leaf damage locally on a drone, while full disease probability maps may be rendered in the cloud using satellite composites and weather forecasts [37].

These architectures also support plug-and-play functionality, where specific crop modules (e.g., for corn or cotton) or regional sub-models can be swapped, retrained, or updated independently. This modularity ensures adaptability to new disease strains, farming innovations, or regulatory changes without redesigning entire systems [38].

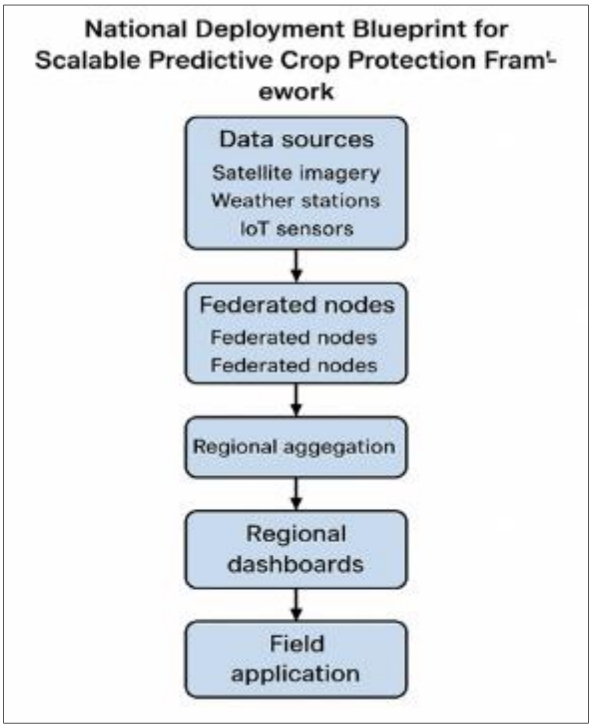

Figure 3 National Deployment Blueprint for Scalable Predictive Crop Protection Framework

Together, federated learning and modular systems offer a secure, flexible, and scalable foundation for predictive crop protection—enabling robust deployment across thousands of farms, while honoring the diversity and specificity inherent in U.S. agriculture [39].

8. Challenges and policy considerations

8.1. Farmer Adoption Barriers and Digital Literacy

Despite the promise of AI-powered predictive tools in agriculture, adoption at the farm level remains uneven, particularly among small and medium-sized producers. One of the key barriers is limited digital literacy, especially in rural areas where access to training and technical support is constrained [30]. Many farmers are unfamiliar with data-driven platforms or skeptical of their reliability, preferring traditional scouting methods and personal expertise honed over years of experience.

Studies show that even when predictive tools are introduced via extension services, user engagement often drops after initial trials unless continuous support and demonstrable value are maintained [31]. Farmers may find platforms complex, cluttered, or poorly adapted to their workflows. Moreover, the “black box” nature of some AI systems—especially those based on deep learning—erodes trust, as users cannot interpret how decisions are derived or validated [52].

Cost also remains a deterrent. While some services are subsidized or offered through cooperatives, many predictive tools rely on subscriptions, specialized hardware (e.g., IoT sensors), or premium analytics, which may be prohibitive for smaller farms. Additionally, concerns about internet access and device compatibility—particularly for edge-based or mobile applications—further limit uptake in low-bandwidth areas [33].

Overcoming these barriers requires human-centered design, localized training programs, and co-creation of tools with farmers and extension agents. Embedding AI interfaces into platforms farmers already use (e.g., yield monitors, weather apps) and providing low-tech alternatives such as SMS-based alerts can broaden participation. Farmer feedback loops, visual explainability, and multilingual interfaces are also vital to building long-term adoption and digital confidence among diverse user groups [34].

8.2. Privacy, Data Ownership, and Ethical Use of Predictive Tools

As agricultural systems become increasingly digitized, the ethical and legal dimensions of data privacy, ownership, and algorithmic accountability take on heightened importance. Farmers are generating more data than ever—through sensors, GPS equipment, drones, and mobile applications—but many remain unclear about who owns, controls, or profits from that information [35].

In the absence of strong national regulation, data is often governed by vendor contracts or proprietary software licenses, which may grant service providers unrestricted access to farm-level analytics. This has raised concerns that sensitive agronomic data could be sold to third parties, used for targeted marketing, or incorporated into broader datasets without consent [36]. Issues of data asymmetry—where corporations accumulate massive datasets while individual farmers receive limited insights—have further intensified skepticism.

Another concern is algorithmic fairness. Predictive tools must be assessed not just for technical accuracy, but also for social equity and transparency. For example, models that disproportionately favor high-input, large-scale operations may widen the digital divide and marginalize smallholder farmers [37]. Ethical deployment requires careful consideration of bias in training data, cultural relevance of decision-support outputs, and inclusion of diverse farming systems in model validation.

Establishing clear data governance frameworks, consent protocols, and transparency standards is essential. Initiatives like the Ag Data Transparent Certification provide guidance, but broader industry alignment and regulatory oversight will be necessary to ensure predictive agriculture advances in ways that are fair, inclusive, and ethically sound [38].

8.3. Policy Incentives and AI-Agriculture Standards

To fully realize the benefits of AI in agriculture, supportive public policy and regulatory frameworks are needed to address adoption barriers, encourage innovation, and ensure responsible deployment. At present, the policy environment for agricultural AI is fragmented, with few standardized benchmarks for model validation, risk classification, or cross-platform interoperability [39].

Governments can play a transformative role by offering incentives for AI adoption, particularly among resource-limited farms. These could include cost-sharing programs for precision hardware, tax credits for digital infrastructure upgrades, and subsidies for farmer participation in AI training or pilot programs. By lowering entry costs and supporting early adoption, public incentives can accelerate scale while ensuring that tools serve a broad spectrum of producers [40].

Another urgent priority is the development of national and international standards for AI applications in agriculture. These standards should outline technical protocols for data interoperability, evaluation metrics for model performance, and safeguards for cybersecurity and ethical compliance. Existing frameworks—such as those proposed by ISO and FAO—offer starting points, but need to be tailored for crop-specific, climate-sensitive applications [41].

Public-private collaborations, modeled on initiatives like the OpenTEAM project or USDA's Partnerships for Climate-Smart Commodities, demonstrate how shared infrastructure and co-developed standards can enhance alignment. Long-term success depends on policies that not only regulate but also enable innovation, ensuring AI solutions remain trusted, inclusive, and aligned with food security and environmental goals [42].

9. Conclusion

9.1. Summary of Findings and Technological Contributions

This study has explored the development and deployment of ML-based predictive frameworks for crop protection, offering a comprehensive view of how data-driven tools can anticipate, mitigate, and manage biotic threats in major U.S. cropping systems. By integrating historical datasets, satellite imagery, sensor outputs, and environmental variables, the research demonstrated how supervised learning models—such as random forests, gradient boosting, and deep neural networks—can forecast disease and pest outbreaks with high accuracy, often providing a lead time of 10–14 days before visible symptoms appear.

The technological contributions of the study are multifold. First, it establishes a modular architecture for predictive analytics that is adaptable to regional agroecological differences and crop-specific disease cycles. Second, it showcases real-time deployment strategies using edge computing and IoT integration, highlighting the feasibility of field-level predictions even in connectivity-limited environments. Third, it emphasizes cloud-based dashboards and mobile decision support systems as tools for multi-field monitoring, regional surveillance, and farmer engagement.

The inclusion of case studies—covering corn in the Midwest, soybean rust in the Southeast, and wheat rust in the Great Plains—validated the system's operational value through yield savings, reduced pesticide usage, and improved forecasting accuracy. Together, these contributions illustrate a scalable model for proactive crop protection that combines technical rigor with practical usability, laying the foundation for a new generation of precision agriculture tools focused on prevention, resilience, and sustainability.

9.2. Relevance to National Agricultural Resilience and Food Security

In the face of mounting climate variability, emerging pest pressures, and supply chain vulnerabilities, predictive analytics for crop protection have become more than a technical innovation—they are a strategic imperative for national agricultural resilience. This study underscores the pivotal role of AI-driven systems in enabling U.S. producers to shift from reactive to anticipatory management practices, thereby enhancing the country's capacity to maintain stable crop yields, reduce input dependencies, and respond swiftly to environmental disruptions.

These systems contribute directly to food security by safeguarding yields against major loss events such as rust outbreaks, invasive pest swarms, and fungal diseases that could otherwise undermine food availability and affordability. Predictive alerts allow farmers to intervene precisely and early, reducing the likelihood of catastrophic losses and buffering against market shocks. By integrating disease forecasts with economic decision-support tools, the frameworks developed in this study also support risk management planning at both the farm and policy levels.

Furthermore, national resilience is strengthened when surveillance systems are interconnected across states and production zones, allowing for coordinated responses to regional threats. Scalable models and federated learning architectures offer a pathway for real-time knowledge transfer without sacrificing data privacy or local specificity. As agriculture intersects increasingly with issues of climate policy, trade, and health, predictive crop protection frameworks offer a strategic technology that aligns environmental sustainability with food system stability—contributing not only to farm-level productivity but also to broader public welfare and national preparedness.

9.3. Call for Future Research and System Integration at Scale

While this study has demonstrated the efficacy of ML-driven crop protection systems, future research is essential to ensure their longevity, fairness, and adaptability. One priority is the integration of diverse data sources, including farmer-reported metrics, economic outcomes, and real-time field anomalies, to enrich model learning and improve contextual relevance. Additional work is also needed to refine interpretability methods so that farmers and advisors can understand, trust, and adjust recommendations based on local expertise.

Scaling these systems nationally will require coordinated investments in digital infrastructure, open data standards, and workforce development. Future research should focus on interoperable frameworks that allow multiple stakeholders—growers, researchers, extension agents, and policymakers—to share and act upon insights in a timely, secure manner. Investigating the long-term economic impacts, environmental trade-offs, and equity implications of predictive systems will also be critical for responsible deployment.

Moreover, a robust governance framework should accompany technical scaling, ensuring that ethical use, data rights, and benefit sharing are embedded into the design of AI-agriculture platforms. As agriculture enters a new era of digital transformation, the integration of predictive crop protection into mainstream decision-making will not only protect yields but redefine how resilience and sustainability are operationalized at scale.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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