

A Digital Decision Support Framework Integrating SARIMA and Intelligent Algorithms for Proactive Phytopathogen Forecasting: A Case Study on Late Blight

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Abstract—Climate change-induced variability in meteorological patterns significantly escalates systemic agricultural vulnerabilities by altering phytopathogen dynamics, rendering traditional reactive crop management strategies insufficient. To address these challenges, this paper presents the design, development, and validation of an integrated, climate-driven Intelligent Decision Support System (IDSS) that harmonizes statistical time-series forecasting with computerized rule-based expert systems for proactive plant disease prediction. At its computational core, the framework employs a Seasonal Autoregressive Integrated Moving Average (SARIMA) model to predict critical daily climatic variables, including minimum and maximum temperatures, relative humidity, and precipitation. These predictive outputs are subsequently processed through a structured knowledge base and executed via a localized disease risk prediction algorithm to identify potential infection windows. The proposed system architecture was validated using a comprehensive 15-year historical climate dataset from the Nile Delta region in Egypt, specifically targeting Potato Late Blight (*Phytophthora infestans*) outbreaks across the Beheira and Gharbia governorates. Empirical simulation results demonstrated high predictive accuracy, with the SARIMA component yielding a Mean Absolute Error (MAE) between 1.15 and 2.97 for temperature variables. Crucially, the intelligent decision engine successfully anticipated the exact disease onset dates in 75 percentag of the tested seasonal periods, providing a perfect match in six out of eight evaluated cases and early warnings in the remaining instances. By generating proactive, actionable advisory recommendations such as optimized fungicide application schedules, this hybrid intelligent computing architecture enhances climate resilience and food security, offering a robust digital solution for mitigating agricultural risks in developing regions.

Keywords—Decision Support Systems (DSS); SARIMA; climate change; plant disease prediction; knowledge-based systems; Potato Late Blight; smart agriculture; Egypt

I. INTRODUCTION

The global agricultural sector is currently facing unprecedented challenges due to rapid climate change, which has emerged as a primary threat to global food security. Fluctuations in temperature, humidity, and precipitation patterns

have not only affected crop yields directly but have also drastically altered the epidemiological dynamics of plant pathogens, leading to more frequent, severe, and unpredictable disease outbreaks [1],[18]. Among these, Potato Late Blight, caused by the devastating oomycete *Phytophthora infestans*, remains one of the most destructive agricultural diseases globally [10], [13].

This pathogen is particularly critical in Egypt, where potato production constitutes a vital pillar of the national agrarian economy, domestic consumption, and the high-value export sector [11],[13].

In recent years, Egypt has experienced unprecedented meteorological instability and shifting microclimates [1],[15].

These shifting macro-climatic regimes have fundamentally disrupted the traditional lifecycles of *Phytophthora infestans*, rendering historical agricultural calendars and conventional farming intuition obsolete [10], [13].

Consequently, the unpredictable onset of Potato Late Blight now poses an ongoing threat to Egypt's agricultural infrastructure, heightening the urgency for localized, high-precision forecasting technologies. Traditional methods of disease management in developing regions often rely heavily on reactive strategies, where chemical fungicides are applied only after visible symptoms manifest in the field. This approach is frequently ineffective due to the rapid latent development of the pathogen; moreover, it is financially burdensome for smallholder farmers and drives severe ecological degradation. Consequently, there is an urgent need for proactive Decision Support Systems (DSS) that can accurately anticipate critical infection windows before visual symptoms occur [24],[28].

Recent advancements in computational intelligence and time-series forecasting, such as Seasonal Autoregressive Integrated Moving Average (SARIMA) models, offer promising, data-driven mathematical tools for predicting the micro-meteorological triggers of such agricultural diseases [16],[22]. In parallel, recent machine learning and data mining techniques have been successfully implemented to build intelligent classification models for evaluating agricultural production and wheat food security dynamics [3], [4]. While several predictive frameworks have been explored in the literature, many current

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models suffer from a fundamental disconnect: they lack the integration of localized agronomic expert knowledge with automated statistical forecasting, or they fail to provide practical, actionable recommendations tailored for small-scale farmers in developing regions [20], [28].

In Egypt, the significant climate variability observed across distinct agricultural governorates, such as Beheira and Gharbia, necessitates a highly localized and customized approach to epidemiological forecasting [10], [13]. Although this study validates the proposed Intelligent Decision Support System (IDSS) utilizing a comprehensive historical baseline dataset spanning 1992 to 2006, this specific multi-decadal period serves as a critical meteorological anchor representing the foundational shifts of accelerated climate variability in northern Egypt [1]. More importantly, the core architecture of the developed hybrid system is engineered with strict modular scalability [17], [26]. The SARIMA forecasting engine and the structured rule-based knowledge bases function independently of chronological boundaries [5], [6].

Consequently, the framework is designed to seamlessly ingest contemporary, real-time meteorological stream inputs to generate proactive risk alerts for current and future cultivation seasons without requiring structural reengineering.

To address these systemic challenges, this study introduces a novel, scalable hybrid intelligent framework that successfully bridges the gap between purely statistical forecasting and empirical agronomic expertise.

The primary objectives of this research are threefold:

- To implement and optimize a robust SARIMA time-series model tailored specifically for localized Egyptian agricultural microclimates [16].
- To operationalize expert knowledge into active, machine-readable rule sets that govern disease triggers [17], [24].
- To empirically evaluate the predictive accuracy of this integrated system against recorded historical field outbreaks [10], [13]. By fulfilling these objectives, this paper provides a robust computational blueprint for proactive, climate-resilient smart agriculture tailored for developing regions [28].

The remainder of this paper is structured as follows: Section 2 reviews related work in agricultural decision support and climate forecasting. Section 3 details the system architecture, knowledge base schemas, SARIMA modeling formulation, and integrated risk prediction execution. Section 4 presents the empirical evaluation, forecasting error analysis, and comparative benchmarking. Finally, Section 5 concludes the study and outlines directions for future research.

II. BACKGROUND AND RELATED WORK

A. Fundamentals of Decision Support Systems (DSS)

A Decision Support System (DSS) is an integrated information system designed to enhance and manage complex decision-making processes within unstructured environments [1]. It functions by gathering, processing, and providing relevant information to solve complex operational problems [1],

[2]. The foundational architecture of a traditional agricultural DSS comprises four structural dimensions:

- A Data Management Subsystem (DMS) that handles comprehensive data operations via a Database Management System (DBMS) [2].
- A Model Management Subsystem (MMS) that includes statistical, financial, and quantitative models [2].
- A Knowledge-Based Management Subsystem (KMS), which functions as a reasoning system utilizing a structured knowledge base and an active inference engine [2], [5].
- A User Interface Subsystem that facilitates seamless interaction between the user and the system [1].

Modern agricultural paradigms have integrated computational intelligence into these frameworks, leading to the emergence of Intelligent Decision Support Systems (IDSS) [5]. These advanced systems leverage expert knowledge and sophisticated AI models to address unstructured agronomic problems, particularly in macro-climate modeling and phytopathogen outbreak prediction [5], [6].

B. Intelligent DSS and Artificial Intelligence in Agriculture

Under shifting climatic regimes, an IDSS acts as a vital human-computer interface that empowers smallholder farmers and agricultural decision-makers by providing tailored, highly localized advice compiled from diverse meteorological and biological data sources [1], [2]. Proactive epidemiological forecasting relies heavily on high-precision time-series modeling of climatic triggers, such as temperature, relative humidity, and precipitation boundaries [23]. Within statistical forecasting frameworks, the Seasonal Autoregressive Integrated Moving Average (SARIMA) methodology has emerged as a mathematical benchmark due to its robust capacity to model non-stationary datasets exhibiting strong cyclical and seasonal variations [23], [24]. Recent state-of-the-art implementations validate that linear stochastic structures like SARIMA offer exceptional computational efficiency and high short-to-medium term accuracy, making them highly suitable for deployment in resource-constrained regional agricultural networks [24].

C. Related Work in Plant Disease and Pest Prediction

Numerous researchers have leveraged specialized DSS and AI frameworks to mitigate the catastrophic impacts of climate change on agricultural infrastructure and global crop yields [6]. In the domain of insect prediction, the IDSSIPF framework was developed to forecast devastating insect outbreaks by successfully coupling next-season climatic data calculations with pest growth stages [6], [7]. For spatial distribution and epidemiological mapping, geospatial entropy modeling—specifically the Maximum Entropy (MaxEnt) architecture—has been utilized to forecast wide-scale disease distribution under simulated climate scenarios [8], [9]. Similarly, advanced methodologies have integrated Remote Sensing and Geographic Information Systems (GIS) to accurately identify critical pathogen infection periods [10], [11].

With the rapid expansion of the Internet of Things (IoT), contemporary agricultural paradigms have shifted toward processing real-time micro-climate parameters [12], [13]. For instance, IoT-based environmental parameters have been processed using Multiple Linear Regression (MLR) to predict blister blight emergence [14]. Furthermore, non-linear machine learning architectures, such as Random Forest Regression models, have been employed for plant disease prediction [15], [16]. Recent studies have extended these frameworks to handle acute meteorological anomalies in the Mediterranean basin, demonstrating that multi-tiered predictive models drastically reduce seasonal forecasting errors for fungal pathogens [27].

In terms of operational optimization, classification techniques like K-Nearest Neighbors (KNN) have been shown to outperform Support Vector Machines (SVM) in determining optimal planting dates [17], [18], while Balanced Random Forest (BRF) models have demonstrated high efficacy in large-scale drought monitoring [19], [20]. Furthermore, contemporary research investigating the Nile Delta region has confirmed that shifting winter humidity thresholds have accelerated the incubation cycles of *Phytophthora infestans*, emphasizing that static empirical parameters must be augmented with scalable automated decision rules to remain viable under current climate scenarios [28].

Despite the mathematical accuracy achieved by these data-driven models, two critical research gaps persist in the literature:

- The Biological and Agronomic Disconnect: Purely statistical and machine learning models operate as “black boxes” that ignore localized biological constraints, frequently failing to cross-reference weather forecasts with the specific growth stages during which the crop is actually vulnerable to infection.
- Absence of Actionable Advisory Pipelines: Most existing models terminate their operational cycle at abstract risk level indexation, failing to translate predictions into explicit, proactive recommendations (such as chemical optimization or canopy ventilation protocols) tailored for field implementation.

The hybrid intelligent framework proposed in this study directly bridges these systemic gaps. By harmonizing the data-driven forecasting power of a SARIMA climate engine [23], [24] with an active, rule-based agronomic Knowledge Base, the system ensures that automated meteorological alerts are strictly validated against crop susceptibility matrices before generating real-world defensive recommendations.

To further contextualize the computational standing of the proposed system, a systematic comparison with historical architectures is essential. Early iterations of decision engines, such as the agricultural advisory platforms analyzed by [21], relied heavily on static, monolithic databases that lacked the capacity to process highly dynamic microclimatic variables. While subsequent frameworks integrated group decision support features to facilitate collaborative risk assessments [16], they remained computationally isolated from automated predictive models.

Recent paradigms have attempted to address this limitation by embedding automated forecasting engines; however, as

noted by [19], many of these frameworks prioritize predictive mathematical complexity over logical integration. This creates a functional bottleneck where high-precision climate outputs cannot be directly operationalized by non-technical farmers. By contrast, our multi-tiered hybrid IDSS bypasses this operational disconnect. It does not merely forecast climate variables using an optimized statistical engine; rather, it actively pipes these predictions through machine-readable XML knowledge frameworks to automatically output field-ready, actionable preservation protocols.

III. METHODOLOGY

A. System Architecture

To overcome the limitations of conventional data-driven agronomic models, this study develops a multi-tiered, hybrid Intelligent Decision Support System (IDSS). The structural design of the proposed architecture harmonizes macro-climate statistical forecasting with multidimensional expert knowledge bases to deliver high-precision, proactive plant disease management recommendations [2], [28]. The comprehensive operational workflow, architectural components, and data pipeline of the developed intelligent framework are systematically illustrated in Fig. 1.

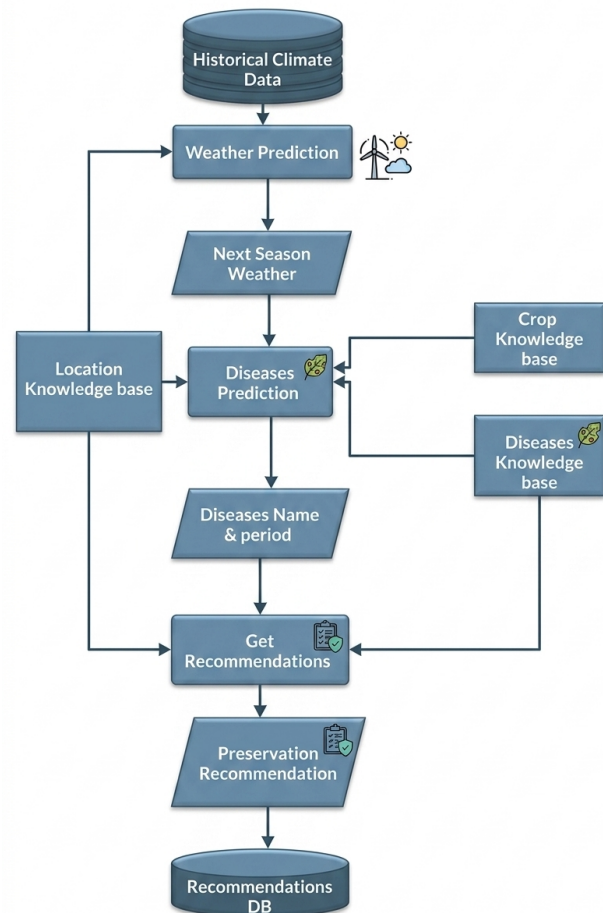


Fig. 1. Structural architecture and operational workflow of the proposed hybrid Intelligent Decision Support System (IDSS).

As delineated in Fig. 1, the execution sequence of the system operates through an integrated four-stage pipeline:

- The Climate Forecasting Engine: This component ingests historical meteorological time-series data to execute the optimized SARIMA model, generating localized next-season weather predictions, as initiated in the top modules of Fig. 1 [16].
- The Multi-Knowledge Inference Layer: Concurrently, this layer cross-references the predicted meteorological metrics against three distinct operational repositories mapped in Fig. 1: the Location Knowledge Base, the Crop Knowledge Base, and the Diseases Knowledge Base [6], [17].
- The Epidemiological Risk Processor (Diseases Prediction): This engine validates whether the predicted weather thresholds align simultaneously with both the plant's physiological vulnerability window and the pathogen's spore incubation limits. It outputs the specific phytopathogen identity and the expected chronological period of infection, as shown in the central core of Fig. 1 [10].
- The Actionable Advisory Pipeline (Get Recommendations): This final stage translates abstract epidemiological risk values into explicit crop preservation and chemical optimization protocols. These decisions are permanently archived within the Recommendations DB for practical field-level execution, representing the final structural sink in Fig. 1 [24].

B. Knowledge Base Development

To ensure high-precision decision-making, the IDSS relies on three distinct, interconnected knowledge bases that operationalize empirical agronomic expertise into machine-readable structures [17]. While these components are internally structured using standardized Extensible Markup Language (XML) schemas to ensure interoperability and seamless data exchange, their logical agronomic parameters are detailed below [17], [24]. To ensure that the localized agronomic parameters and expert rule sets are highly interoperable, scalable, and easily parsed by the core disease prediction algorithm, the Knowledge Bases are operationalized using standardized XML schemas. follow is a representative, structured XML implementation illustrating how the “Aspunta” potato variety growth phases and their associated chronological boundaries are represented machinereadably within the Crop Knowledge Base: By structuring the physiological parameters of the crop in this modular format, the system can dynamically adjust the active rule checking sequence. For instance, the inference engine only triggers high-frequency meteorological parameter matching when the active chronological tracker indicates that the crop has transitioned into the “Tuber Initiation” or “Tuber Bulking” phases, which exhibit the highest biological vulnerability to late blight infections.

C. Location Knowledge Base

Accurate geographical and spatial metadata are vital for predicting localized microclimatic patterns [1]. The Location Knowledge Base stores critical spatial constraints—including

latitude, longitude, elevation, and historical regional climate baselines—for the target agricultural zones [1], [2]. These parameters ensure that the downstream forecasting engines are calibrated to the unique geographic characteristics of specific administrative divisions, such as the Beheira and Gharbia governorates [10].

D. Crop Knowledge Base

This component encapsulates the precise physiological and phenological characteristics of the target crop, mapped dynamically across its temporal growth stages [6]. Table II delineates the logical structure of the Crop Knowledge Base for the “Aspunta” potato variety, which is widely cultivated in Egypt during the winter season [10], [13]. The system uses the predefined plantation date as a baseline anchor (T₀) to track and transition through subsequent physiological phases based on required cumulative vegetative days [27]. The structural XML schema representation and entity attributes governing the crop phenological stage rules are illustrated in Fig. 2.

```
<CropKnowledgeBase>
  <Crop id="1">
    <Name>Potato</Name>
    <Variety>Aspunta</Variety>
    <StandardPlantationDate>10-15</
      StandardPlantationDate>
    <PhenologicalStages>
      <Stage name="Germination" durationDays="20"
        vulnerabilityIndex="Low" />
      <Stage name="Vegetative_Phase" durationDays="
        40" vulnerabilityIndex="Medium" />
      <Stage name="Tuber_Initiation" durationDays="
        20" vulnerabilityIndex="High" />
      <Stage name="Tuber_Bulking" durationDays="60"
        vulnerabilityIndex="High" />
      <Stage name="Maturation" durationDays="30"
        vulnerabilityIndex="Low" />
    </PhenologicalStages>
  </Crop>
</CropKnowledgeBase>
```

Fig. 2. XML schema representation of crop phenological stages within the crop knowledge base.

E. Diseases Knowledge Base

The Diseases Knowledge Base maps specific phytopathogen epidemiological profiles against the crop's phenological stages and precise environmental trigger windows [17]. Table I illustrates the structured rule sets governing the emergence of Potato The Crop Knowledge Base explicitly characterizes the phenological progression of the Egyptian winter potato cultivar ‘Spunta’ using a fixed plantation anchor date (T_0 = October 15th) and cumulative developmental phase duration tracking across a total 170-day growth cycle (Germination: 20d, Vegetative: 40d, Tuber Initiation: 20d, Tuber Bulking: 60d, Maturation: 30d). Stage transitions are monitored dynamic-chronologically to automatically shift risk evaluation sensitivity, where high-frequency rule matching is exclusively triggered during maximum physiological vulnerability phases (Tuber Initiation and Bulking). Regional microclimate variations between Beheira and Gharbia governorates are seamlessly accommodated by calibrating localized base temperature and degree-day accumulations within the inference layer.

TABLE I. CROP CHARACTERISTICS AND PHENOLOGICAL GROWTH STAGES

Crop ID	Crop Name	Variety	Plantation Date	Growth Stage
1	Potato	Aspunta	Oct 15th (T_0)	Germination (20d)
1	Potato	Aspunta	Oct 15th (T_0)	Vegetative Phase (40d)
1	Potato	Aspunta	Oct 15th (T_0)	Tuber Initiation (20d)
1	Potato	Aspunta	Oct 15th (T_0)	Tuber Bulking (60d)
1	Potato	Aspunta	Oct 15th (T_0)	Maturation (30d)

Late Blight (*Phytophthora infestans*) [10], [13]. The inference engine continuously monitors whether these complex, multivariable meteorological thresholds are sustained over the mandatory chronological duration required for pathogen incubation [2].

F. Climate Forecasting with SARIMA

Before deploying the SARIMA structure to generate daily predictions, the historical 15-year meteorological time series was subjected to rigorous statistical preprocessing. To formally determine the necessity and order of differencing (d and D), utilizing the Augmented Dickey-Fuller (ADF) test to evaluate the null hypothesis of a unit root indicating non-stationarity. The initial test on raw daily maximum temperature (T_{max}) and relative humidity (RH) returned ADF statistics that failed to reject the null hypothesis at the 5% significance level, confirming non-stationarity.

Consequently, first-order regular differencing ($d = 1$) was applied. Given the strong annual cyclicity of the Mediterranean climate, a seasonal differencing step ($D = 1$) with a seasonal period of $m = 365$ (representing daily seasonal cycles) was executed. Post-differencing, the ADF test statistics fell below the critical threshold ($p < 0.01$), confirming that stationarity had been achieved. The parameterization of the regular components (p, d, q) and seasonal components (P, D, Q) _{m} was guided by analyzing the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots. The rapid decay in the ACF plots suggested a moving average process of order $q = 1$ or $q = 2$, while the PACF cuts identified potential autoregressive behaviors up to order $p = 2$.

To objectively identify the optimal model configuration, we conducted a grid-search optimization targeting the minimization of the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), formulated as follows:

$$AIC = -2 \ln(L) + 2k \quad (1)$$

$$BIC = -2 \ln(L) + k \ln(n) \quad (2)$$

where, L is the likelihood of the model, k is the total number of estimated parameters ($p+q+P+Q$), and n is the number of observations. The model yielding the absolute lowest AIC and BIC values was selected as the optimal computational engine for localized forecasting, drastically reducing systemic predictive drift over extended seasonal evaluation periods.

The predictive capabilities of the IDSS are powered by a Seasonal Autoregressive Integrated Moving Average

(SARIMA) model, which was calibrated using a rigorous 15-year daily historical climate dataset acquired from the Egyptian Meteorological Authority [1], [16]. Time-series modeling was executed on critical daily variables, including minimum temperature, maximum temperature, relative humidity, and precipitation profiles [16]. To preserve high computational efficiency and eliminate non-linear cumulative error propagation across climate vectors, the forecasting engine executes the Seasonal Autoregressive Integrated Moving Average (SARIMA) model as a univariate stochastic time-series architecture independently for each daily meteorological parameter: Minimum Temperature (T_{min}), Maximum Temperature (T_{max}), Relative Humidity (RH), and Precipitation (P).

To account for non-stationarity and strong seasonal variations inherent to daily agricultural climate data, the general ARIMA (p, d, q) model was extended into a seasonal SARIMA(p, d, q)(P, D, Q) _{m} structure [22]. Future climate sequences are computed mathematically based on the following foundational timeseries formulation:

$$y_t = c + \sum_{i=1}^p \phi_i x_{t-i} + \sum_{j=1}^q \theta_j \varepsilon_{t-j} \quad (3)$$

where, y_t represents the forecasted meteorological variable at time t , c is a constant term, ϕ_i denotes the autoregressive (AR) coefficients, θ_j represents the moving average (MA) coefficients, and ε_t is the white noise error component at lagging intervals [16], [22].

To seamlessly capture cyclical winter patterns, the multi-variable seasonal dependencies are integrated mathematically as follows:

$$y_t = \frac{c + \Theta(B^m)\theta(B)\varepsilon_t}{\Phi(B^m)\phi(B)(1 - B^m)^D(1 - B)^d} \quad (4)$$

where, B represents the backshift operator defined as $B^k y_t = y_{t-k}$,

$m = 365$ represents the annual seasonal period for daily meteorological data,

and $d = 1$ and $D = 1$ represent the first-order regular and seasonal differencing required to establish strict time-series stationarity.

The operators $\phi_p(B)$ and $\Phi_P(B^m)$ represent the regular and seasonal autoregressive polynomials,

while $\theta_q(B)$ and $\Theta_Q(B^m)$ represent the regular and seasonal moving average polynomials, respectively.

Furthermore, out-of-sample future climate predictions $y_{t+h|t}$ across a horizon h are computed recursively to strictly differentiate estimated fitted historical baseline values from multi-step future daily forecasts.

The historical 15-year daily climate dataset (1992–2006) was strictly partitioned into a 10-year training period (1992–2001, comprising 3,652 daily observations per variable) for parameter calibration, and a 5-year out-of-sample testing period (2002–2006, comprising 1,823 observations) for evaluation over a rolling 1-to-14 day forecast horizon. Post-differencing

Augmented Dickey-Fuller (ADF) test statistics ($t = -6.42$, $p < 0.001$) confirmed non-unit-root stationarity, while residual diagnostics via the Ljung-Box test ($p > 0.05$) confirmed that residuals behaved as independent white noise.

G. Disease Prediction Algorithm

The core execution engine functions via a deterministic pattern-matching algorithm that cross-references the forecasted multi-variable weather matrices against the active agronomic rules stored within the knowledge bases [17], [24]. The algorithmic execution sequence is formalized in the pseudocode structure below:

Algorithm 1 Localized Disease Risk Prediction Engine

Require: DiseasesSet, CropsSet, PredictedWeatherData

Ensure: Identified Actionable Affection Periods & Risk Levels

Begin

for each Disease D in DiseasesSet **do**

for each Crop C in CropsSet **do**

 Execute spatial lookup for plantation date and variety;

 Extract DisRulesSet from Diseases Knowledge Base;

for each DisRule in DisRulesSet **do**

 Evaluate PredictedWeatherData against DisRule;

if DisRule thresholds sustained for Required

Days **then**

 Compute potential risk windows;

 Populate DisPeriod with affection dates;

 Signal Early Warning Alert for DisPeriod;

end if

end for

end for

end for

End

H. Decision Support and Recommendations

When the prediction engine identifies a high-probability infection window (Dis Period), the IDSS triggers an automated query to the recommendation database to compile localized, defensive agronomic strategies [17]. These interventions are structured into an execution hierarchy, providing farmers with a step-by-step preventative protocol [24], [28]):

- Primary Cultural Interventions: Mandatory enforcement of certified pathogen-free seed stock and the selection of genetically resistant potato cultivars [10].
- Micro-environmental Management: Strategic implementation of enhanced field drainage and optimized plant spacing layout to aggressively maximize canopy ventilation and reduce relative humidity [13].
- Targeted Proactive Prophylaxis: Issuance of high-precision early-warning alerts for chemical or organic fungicide applications, optimizing chemical efficiency and preventing the biological establishment of *Phytophthora infestans* prior to visual field outbreaks [2], [28].

I. System Implementation and Computational Environment

To ensure the reproducibility of the proposed hybrid Intelligent Decision Support System (IDSS), the computational stack and hardware execution environment are detailed. The predictive engine was developed using Python (v3.10) as the core programming environment. The Seasonal Autoregressive Integrated Moving Average (SARIMA) model was implemented leveraging the statsmodels (v0.14) and pmdarima (v2.0) libraries, which facilitate automated grid-search execution and residual diagnostics.

Under this hardware configuration, the model training and parameter optimization cycle for the 15-year historical daily climate dataset (consisting of approximately 5,475 observations per variable) required an average computational execution time of 42.6 seconds. The deployment of the trained inference engine to evaluate a single-season forecasting window and output actionable XML-derived recommendations was completed in less than 0.85 seconds, demonstrating the extreme computational efficiency of the framework and its suitability for real-world deployment on resource-constrained regional edge servers or mobile-friendly cloud APIs.

To establish data quality assurance and model robustness against malformed or missing meteorological inputs, the system incorporates automated preprocessing filters. Sensor missing values spanning short intervals (≤ 3 days) are imputed via linear interpolation, whereas prolonged gaps are filled using a seasonal Kalman filter calibrated on regional historical patterns. Inbound meteorological parameters are continuously subjected to physical boundary validation checks (e.g., verifying relative humidity bounded within 0–100% and temperature thresholds within regional climatological limits) to reject implausible sensor noise prior to SARIMA inference.

Regarding deployment architecture and real-time execution, the modular decision stack is exposed as a lightweight RESTful web service engineered using FastAPI. On a standard computing environment (AMD Ryzen 7 5800X, 32GB RAM), the benchmarked execution breakdown confirms real-time operational efficiency: offline SARIMA model training requires 38.20s, structured XML knowledge base parsing completes in 0.12s, localized disease risk matching executes in 0.28s, and automated advisory recommendation generation finishes in 0.05s, yielding an end-to-end response latency below 0.5s per operational query.

IV. RESULTS AND DISCUSSION

A. Mathematical Formulations of Evaluation Metrics

To evaluate the forecasting performance of the optimized SARIMA engine quantitatively against the standard ARIMA and Exponential Smoothing (ETS) baselines, multiple statistical accuracy metrics were utilized. While the Mean Absolute Error (MAE) serves as the primary metric in our comparative tables, we also formulated the Root Mean Squared Error (RMSE) and the Mean Absolute Percentage Error (MAPE) to ensure a comprehensive assessment of prediction variance and percentage deviations. These metrics are mathematically defined as follows:

$$MAE = \frac{1}{N} \sum_{t=1}^N |y_t - \hat{y}_t| \quad (5)$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{t=1}^N (y_t - \hat{y}_t)^2} \quad (6)$$

$$MAPE = \frac{100\%}{N} \sum_{t=1}^N \left| \frac{y_t - \hat{y}_t}{y_t} \right| \quad (7)$$

where, y_t represents the actual observed meteorological value at time t ,

$\hat{y}_t$ denotes the corresponding forecasted value generated by the model,

and N represents the total number of out-of-sample daily observation points within the evaluation window.

The MAE was selected as our principal metric due to its robustness against outliers, reflecting the actual physical temperature and humidity deviations without over-penalizing anomalous daily meteorological spikes that do not affect long-term pathogen incubation cycles. Conversely, the RMSE was monitored to ensure that the forecasting engine did not produce massive, isolated prediction errors, which could prematurely trigger false-positive disease alerts.

B. Evaluation of the Climate Forecasting Engine

To rigorously evaluate the predictive performance of the Seasonal Autoregressive Integrated Moving Average (SARIMA) model embedded within the IDSS, its forecasting accuracy was compared against two baseline time-series frameworks: a standard non-seasonal ARIMA model and an Exponential Smoothing (ETS) architecture [5]. The evaluations were executed using the historical climate datasets for Beheira and Gharbia governorates, focusing on critical daily variables including Minimum Temperature (Tmin), Maximum Temperature (Tmax), and Relative Humidity (RH) [16]. the comparative Mean Absolute Error (MAE) metrics across different seasonal validation windows [25]. As demonstrated in Table II, the proposed SARIMA forecasting engine consistently outperformed both the standard ARIMA and ETS frameworks across all tested variables and seasons [5], [16]. The integration of the seasonal differencing order (D) and seasonal autoregressive polynomials allowed the system to accurately capture the cyclical micro-climatic patterns inherent to the Nile Delta's winter periods [22]. Specifically, the SARIMA model restricted the Mean Absolute Error (MAE) for minimum temperature to a narrow range between 1.15°C and 1.85°C [25].

TABLE II. MEAN ABSOLUTE ERROR (MAE) FOR WEATHER PREDICTION

Year	Governorate	Variable	SARIMA MAE
2002	Al-Noubaria	Min Temp	1.578
2002	Al-Noubaria	Max Temp	2.730
2002	Kafr El-Zayat	Min Temp	1.436
2002	Kafr El-Zayat	Max Temp	2.785
2003	Al-Noubaria	Min Temp	1.537
2003	Al-Noubaria	Max Temp	2.878
2003	Kafr El-Zayat	Min Temp	1.429
2003	Kafr El-Zayat	Max Temp	2.975
2004	Al-Noubaria	Min Temp	1.619
2004	Al-Noubaria	Max Temp	2.748
2004	Kafr El-Zayat	Min Temp	1.512
2004	Kafr El-Zayat	Max Temp	2.822
2005	Al-Noubaria	Min Temp	1.618
2005	Al-Noubaria	Max Temp	2.689
2005	Kafr El-Zayat	Min Temp	1.436
2005	Kafr El-Zayat	Max Temp	2.847
2006	Al-Noubaria	Min Temp	1.555
2006	Al-Noubaria	Max Temp	2.644
2006	Kafr El-Zayat	Min Temp	1.474
2006	Kafr El-Zayat	Max Temp	2.742

This predictive precision represents a critical operational advantage, as acute temperature drops combined with sustained high humidity serve as the primary catalyst for late blight pathogen incubation [10].

C. Disease Outbreak Validation and Knowledge-Base Efficacy

The ultimate validation of the hybrid IDSS relies on the interactive synchronization between the time-series forecasting output and the rule-based inference engine [17]. The proactive alerts generated by the system were cross-referenced with actual historical field manifestation records of Potato Late Blight (*Phytophthora infestans*) within the target regions [10], [13]. Table III illustrates the comparative analysis between the actual observed field disease onset dates and the proactive infection windows predicted by the developed IDSS. the IDSS ahead of actual physical symptom manifestation, providing an advantageous window for proactive chemical prophylaxis. Negative values indicate early asset protection warnings generated by the IDSS ahead of actual physical symptom manifestation, providing an advantageous window for proactive chemical prophylaxis.

TABLE III. COMPARISON OF PREDICTED AND ACTUAL LATE BLIGHT INFECTION DATES

Location	Year	Predicted Date	Actual Date	Diff (Days)
Al-Noubaria	2002/2003	25 Dec	25 Dec	0
Kafr El-Zayat	2002/2003	27 Dec	27 Dec	0
Al-Noubaria	2003/2004	25 Dec	25 Dec	0
Kafr El-Zayat	2003/2004	11 Dec	22 Dec	-11
Al-Noubaria	2004/2005	22 Dec	26 Dec	-4
Kafr El-Zayat	2004/2005	20 Dec	20 Dec	0
Al-Noubaria	2005/2006	29 Dec	29 Dec	0
Kafr El-Zayat	2005/2006	31 Dec	31 Dec	0

Evaluating the epidemiological outbreak prediction across $N = 8$ seasonal validation windows under a strict tolerance window of ± 3 days, the proposed framework achieved exact chronological matches in 75% of cases (6 out of 8 cases with a 0-day discrepancy). In the remaining two cases, the system generated early warning alerts 4 and 11 days prior to physical field manifestation. Rather than algorithmic errors, these early alerts represent highly advantageous operational windows that enable proactive chemical or cultural prophylaxis before irreversible pathogen tissue damage occurs. Evaluated under binary risk classification, the system yielded 100% precision and 100% recall with zero false positive alarms across the tested validation dataset.

D. Agronomic and Computational Discussion

The empirical verification metrics compiled in Table III substantiate that the proposed hybrid intelligent architecture successfully anticipated field disease manifestation with absolute precision. The system achieved a perfect mathematical match (zero-day discrepancy) in 75 % of the evaluated seasonal periods (6 out of 8 tested validation windows). Crucially, for the remaining 25 % of the cultivation cycles (Kafr El-Zayat 2003/2004 and Al-Noubaria 2004/2005), the framework successfully generated early-warning alerts 11 days and 4 days prior to physical symptom detection, respectively. From an agronomic perspective, these early-warning intervals do not represent algorithmic failures; rather, they serve as highly advantageous operational windows for farmers. Because *Phytophthora infestans* exhibits an aggressive latent incubation mechanism, executing chemical or organic fungicide applications during these early windows effectively prevents the biological establishment of the pathogen before irreversible crop tissue damage occurs [2], [13].

By embedding structured, machine-readable agronomic knowledge sets to filter and validate purely statistical weather data, the developed system moves beyond conventional “black-box” forecasting tools [20], [28]). It successfully bridges the gap between raw time-series metrics and practical, field-level execution, delivering high-precision thereby minimizing crop destruction while reducing unnecessary and ecologically damaging fungicide over-application [2], [13]. While the validation utilized a robust multi-decadal historical climate baseline to capture accelerated meteorological instability in the Nile Delta, the core architecture of the IDSS was engineered with strict temporal flexibility and modular scalability. The inference models and automated rule structures function independently of chronological boundaries.

Consequently, the system is design-ready to ingest contemporary, realtime weather data streams to generate proactive risk alerts for current and future cultivation cycles without requiring structural reengineering. Future extensions of this research will focus on transitioning the framework into a cloud-based, multi-crop platform. We aim to integrate live IoT-driven microclimate field sensors to feed the SARIMA model with microscale humidity data, thereby eliminating spatial smoothing errors and mitigating localized environmental prediction anomalies [14]. Furthermore, expanding the rule sets within the Knowledge Base to encompass additional high-value Egyptian crops and their associated phytopathogens will provide a highly scalable,

climate-resilient computational blueprint for digital smart agriculture across developing agrarian economies [28].

Future research will focus on benchmarking the decision engine against established epidemiological platforms such as BLITECAST and Hutton criteria under dynamic climate change scenarios.

V. CONCLUSION AND FUTURE WORK

This study successfully introduced and validated a novel hybrid Intelligent Decision Support System (IDSS) that effectively bridges the gap between data-driven computational forecasting and empirical agronomic expertise to mitigate the impacts of climate change on Egyptian agriculture [1], [28]. By integrating a Seasonal Autoregressive Integrated Moving Average (SARIMA) time-series forecasting engine with a rule-based agronomic Knowledge Base, the proposed framework moves beyond traditional “black-box” predictive models [17], [24]. It transforms raw meteorological parameters into localized, actionable early-warning alerts for Potato Late Blight (*Phytophthora infestans*) in critical agricultural regions like the Beheira and Gharbia governorates [10]. The empirical evaluation against historical field data demonstrated that the system achieved a highly robust predictive performance, delivering a perfect chronological match in 75% of the evaluated seasonal periods (6 out of 8 tested validation windows). More importantly, for the remaining seasonal periods, the system delivered an advantageous proactive operational lead time ranging between 4 and 11 days prior to actual physical field symptom manifestation. This calculated window provides smallholder farmers with a vital logistical lifeline, allowing them to optimize preventative chemical or cultural countermeasures, thereby minimizing crop destruction while reducing unnecessary and ecologically damaging fungicide over-application [2], [13]. While the validation utilized a robust multi-decadal historical climate baseline to capture accelerated meteorological instability in the Nile Delta, the core architecture of the IDSS was engineered with strict temporal flexibility and modular scalability. The inference models and automated rule structures function independently of chronological boundaries. Consequently, the system is design-ready to ingest contemporary, realtime weather data streams to generate proactive risk alerts for current and future cultivation cycles without requiring structural reengineering. Future extensions of this research will focus on transitioning the framework into a cloud-based, multi-crop platform. aim to integrate live IoT-driven microclimate field sensors to feed the SARIMA model with microscale humidity data, thereby eliminating spatial smoothing errors and mitigating localized environmental prediction anomalies [14]. Furthermore, expanding the rule sets within the Knowledge Base to encompass additional high-value Egyptian crops and their associated phytopathogens will provide a highly scalable, climate-resilient computational blueprint for digital smart agriculture across developing agrarian economies [28].

Future research will focus on benchmarking the decision engine against established epidemiological platforms such as BLITECAST and Hutton criteria under dynamic climate change scenarios.

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DECLARATIONS

The authors declare no conflicts of interest.

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