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International Journal of Artificial Intelligence and Machine Learning

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Research Paper Open Access

Spatial Analytics And Machine Learning Integration For African Swine Fever Management: A Predictive And Prescriptive Decision Support Framework

Roger S. Mission

College of Computing and Information Sciences, University of Antique, Philippines. rsmission@antiquespride.edu.ph

Abstract

Background: African Swine Fever (ASF) has severely disrupted the Philippine hog industry since 2019, resulting in the culling of over 300,000 pigs and threatening national food security. Current management strategies are often hindered by inadequate monitoring and weak biosecurity protocols. **Objectives:** This study aims to develop and introduce a web-based Decision Support System (DSS) that integrates Geographic Information Systems (GIS), Density-Based Spatial Clustering of Applications with Noise (DBSCAN), and Random Forest Regressor algorithms to effectively identify disease hotspots and forecast future outbreaks. **Method:** A mixed-methods developmental design was utilized to construct the system. The DSS was subsequently evaluated based on ISO/IEC 25010 standards by a diverse panel of 258 stakeholders comprising policymakers, IT professionals, and veterinarians alongside comprehensive technical audits. **Results:** The system demonstrated high efficacy in distinguishing dense infection clusters from isolated "noise" cases using DBSCAN, while the Random Forest model generated accurate monthly forecasts for ASF cases and mortality. Stakeholders rated the system's functional dimensions from "Acceptable" to "Highly Acceptable," though technical audits identified critical areas requiring performance optimization and cybersecurity hardening. **Conclusion:** The integration of spatial and predictive analytics provides a robust and vital approach to managing ASF outbreaks. The system proves capable of significantly improving disease monitoring and forecasting, despite the need for specific technical refinements. **Contribution:** This research contributes a practical, data-driven framework for enhancing the resilience of the swine industry against ASF. Furthermore, it establishes a technological foundation that prompts and guides future national-level data integration and the expansion of AI capabilities in agricultural epidemiology.

Keyword: African Swine Fever, Decision Support Framework, DBSCAN, GIS, Random Forest

Introduction

The emergence of African Swine Fever (ASF) in the Philippines in July 2019 marked a catastrophic shift for the domestic swine industry, which serves as a cornerstone of rural livelihoods and protein security (Hsu et al., 2023). Characterized by a near 100% mortality rate and the absence of a viable vaccine, the virus has induced severe economic strain, leading to widespread supply shortages and unprecedented price surges. While the national government initiated the "Bantay ASF sa Barangay" program to curb transmission (Fernandez-Colorado, 2024; Hsu et al., 2023), these efforts remain heavily constrained by insufficient spatial intelligence and a lack of data-driven monitoring capabilities.

Building upon the foundational spatial analysis conducted by Mission and Rubio (2024), which established the geographic patterns of the outbreak, this study advances the research by transitioning from passive mapping to an active Decision Support System (DSS). While the previous work focused on the "where" of the disease, this framework addresses the "what next" by delivering descriptive, predictive, and prescriptive analytics. By integrating Geographic Information Systems (GIS), the DBSCAN algorithm, and Random Forest modeling, the system empowers stakeholders to proactively implement targeted biosecurity measures rather than relying on reactive containment. This work directly aligns with the United Nations Sustainable Development Goals, specifically SDG 2 and SDG 8, by fostering a more technologically resilient agricultural framework

MATERIALS AND METHODS

The study employed a mixed-methods approach, combining a descriptive analysis of historical epidemiological data with developmental research guided by a Modified Agile model. The study area focused on Panay Island in the Western Visayas region, utilizing official ASF case data obtained from the Bureau of Animal Industry (BAI) and the World Organization for Animal Health (WOAH, formerly OIE) spanning 2019 to 2023.

Analytical Techniques

The development of the decision support system (DSS) commenced with the aggregation of spatial and non-spatial data, encompassing animal health records, geocoordinates of confirmed ASF cases, historical outbreak patterns, and expert knowledge (Figure 1). Following rigorous data cleaning and integration to ensure analytical consistency, a synergistic framework was established leveraging Business Intelligence (BI), Geographic Information Systems (GIS), the DBSCAN algorithm, and Random Forest modeling.

Within this framework, GIS provides the foundational spatial infrastructure, DBSCAN isolates high-density ASF clusters to pinpoint critical hotspots, and the Random Forest algorithm analyzes underlying risk factors to facilitate targeted interventions. The final development phase involved designing a user-friendly web interface that features interactive GIS maps, risk assessment tools, a symptom checker, and live chat support. Prior to deployment via a secure online portal, the system underwent rigorous usability testing and evaluation against ISO/IEC 25010 standards by veterinarians, policymakers, and farmers.

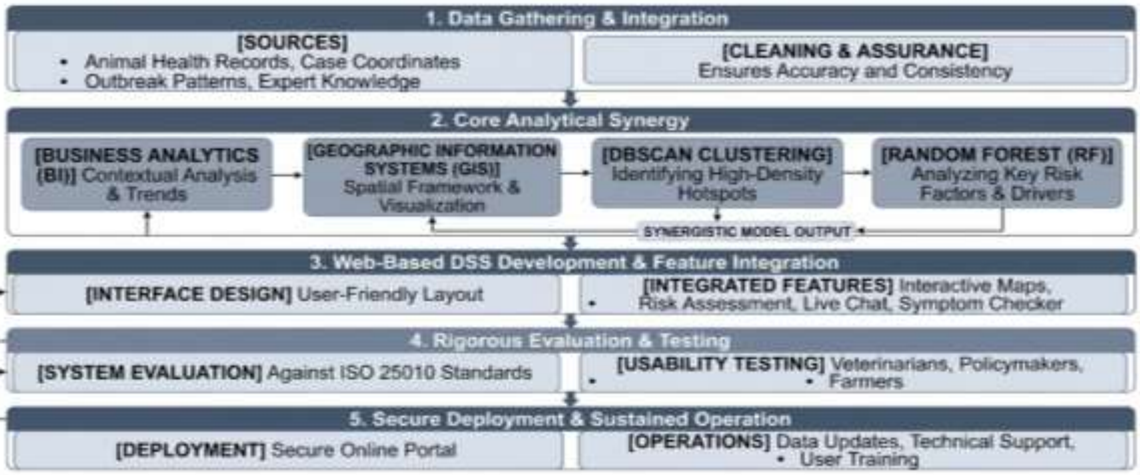

FIGURE 1: Decision Support System Development Methodology

Spatial Clustering Methodology

The Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm was selected as the primary analytical technique for identifying spatial clusters of ASF outbreak locations, as density-based clustering is highly effective for tracking infectious disease transmission hotspots (Lin & Wen, 2022). Initial data preprocessing involved standardizing datetime fields, extracting valid latitude and longitude coordinates, and handling missing records from the raw dataset. The geographic coordinates were subsequently transformed into a numerical array to serve as the input matrix for the clustering algorithm.

Mathematical Formulation of DBSCAN

Let the dataset of preprocessed ASF outbreak locations be defined as D = {x1, x2, …., xn}, where each data point xi represents a geographic coordinate in a two-dimensional spatial domain. The DBSCAN algorithm partitions D based on two primary hyperparameters: the neighborhood radius (implemented computationally as eps), which defines the maximum distance between two neighboring points, and {MinPts} (implemented as min_samples), which specifies the minimum number of neighboring points required to form a cluster.
The algorithm's operational logic is governed by the following formal definitions:

-Neighborhood: The neighborhood of an outbreak location p, denoted as (p), is the set of points situated within a spatial distance from p:

$$N \in (p) = \{q \in D \mid \{dist(p,q) \leq \in\} \quad (1)$$

where {dist}(p,q) represents the geographic distance metric between points p and q.

Core Point Identification: A point q is classified as a core point if the cardinality of its -neighborhood satisfies the minimum sample threshold:

$$| N \in (p) | \geq \{MinPts\} \quad (2)$$

Density-Reachability: A point q is directly density-reachable from point p if q N (p) and p is a core point. Furthermore, q is density-reachable from p if there exists a chain of points p1, p2, ..., pk where p1 = p and pk = q, such that each p{i+1} is directly density-reachable from pi.

Cluster Formation: A spatial cluster C is formulated as a non-empty, maximal subset of D wherein all points are density-connected. Two points p and q are density-connected if there exists a core point o D such that both p and q are density-reachable from o. Points that cannot be density-reached from any core point are classified as noise (outliers).

Visualization and Output

Following the execution of the DBSCAN algorithm, the clustering results are visualized on an interactive map using color-coded markers. This process effectively isolates dense ASF outbreak zones from sporadic occurrences, and the resulting map is exported as an HTML file for further epidemiological analysis.

Algorithmic Workflow and Predictive Modeling Execution

The predictive modeling module processes historical epidemiological data to generate localized, long-term forecasts. Raw outbreak records are first temporally and spatially aggregated by month, year, municipality, and province, incorporating missing value imputation to maintain dataset integrity. A deterministic function then stratifies each geographic unit into predefined risk categories (from 'No Risk' to 'High Risk') based on monthly case volumes.

To generate projections, the system employs a conditional modeling strategy: for municipalities with at least 12 months of recorded data, a Random Forest Regressor projects case and mortality counts over a 72-month horizon, aligning with recent studies demonstrating the efficacy of machine learning in forecasting ASF outbreaks (Choi et al., 2023). For areas with insufficient historical records, a trend-adjusted moving average serves as the baseline predictive model. These localized forecasts are concatenated with historical records to construct a unified dataset for geospatial mapping.

System Architecture and Technology Stack

The system architecture utilizes a robust, multi-tiered technology stack designed to process both standard relational data and complex geospatial analytics (Figure 2). The frontend interface is powered by a PHP-based Content Management System (CMS), facilitating a dynamic web environment for dashboard interaction and map visualization. On the backend, Python handles complex logical processing, data preprocessing, and the execution of the DBSCAN and Random Forest machine learning algorithms. Data storage and retrieval are managed via MySQL, providing a scalable relational database for outbreak records. Finally, the system integrates ArcGIS Pro as the primary engine for spatial analysis, coordinate processing, and the rendering of density-based clustering outputs.

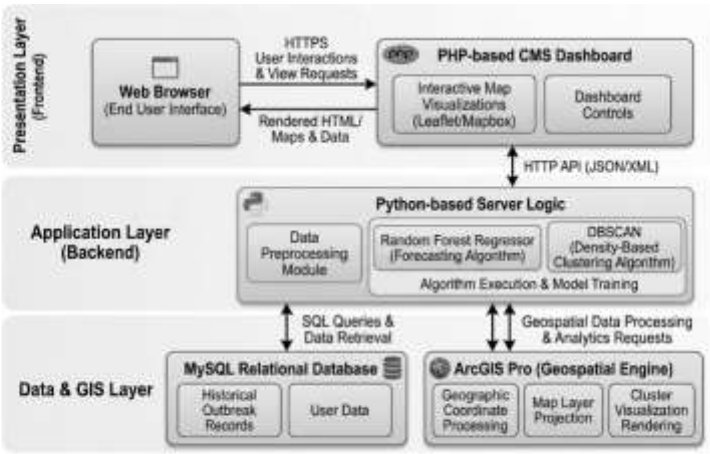

FIGURE 2. System Architecture of Decision Support System

Evaluation Framework

To rigorously assess the operational effectiveness and overall software quality of the developed DSS, the study adopted the ISO/IEC 25010 Systems and Software Quality Requirements and Evaluation (SQuaRE) standard as the primary evaluation framework (Figure 3), consistent with precedent methodologies for evaluating software technology selection and decision support systems (Mission & Rubio, 2024; Rubejes-Silva, 2024).

FIGURE 3. ISO 2510 Evaluation Characteristics

RESULTS AND DISCUSSION

Analytics and Decision Support System Outcomes

Figure 4 presents the descriptive analytics component of the Decision Support System (DSS). These visualizations are fundamentally designed to generate actionable insights by providing a comprehensive overview of historical African Swine Fever (ASF) outbreak patterns and spatial distributions. By synthesizing complex epidemiological data into accessible visual formats, this module aids policymakers, veterinarians, and agricultural stakeholders in formulating evidence-based strategies for managing and mitigating future outbreaks. This end-to-end descriptive process underscores the critical role of data-driven decision-making in effectively addressing the multifaceted challenges posed by ASF.

Figure 5 illustrates the system's transition to proactive disease management through its predictive and prescriptive analytics. The predictive interface displays localized ASF forecasts and emerging high-risk zones generated by the Random Forest Regressor. Utilizing these mathematical projections, the prescriptive component recommends targeted, actionable interventions, such as preemptive quarantines and optimized resource allocation. Furthermore, this framework incorporates iterative stakeholder feedback from veterinarians, policymakers, and farmers, ensuring that the system's rigorous epidemiological models translate into practical, user-centric recommendations for on-the-ground outbreak mitigation.

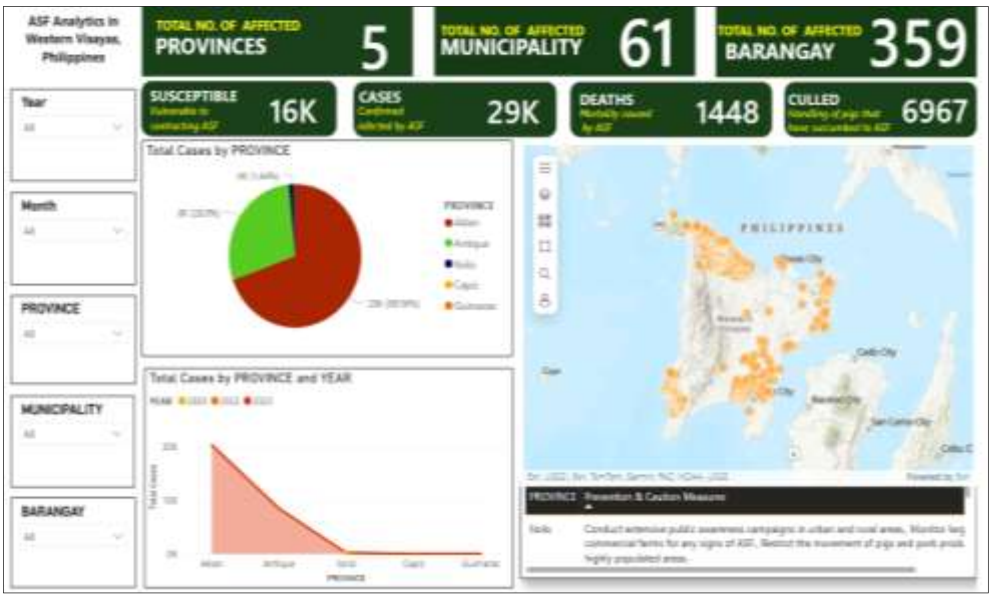

FIGURE 4. Descriptive Analytics of DSS

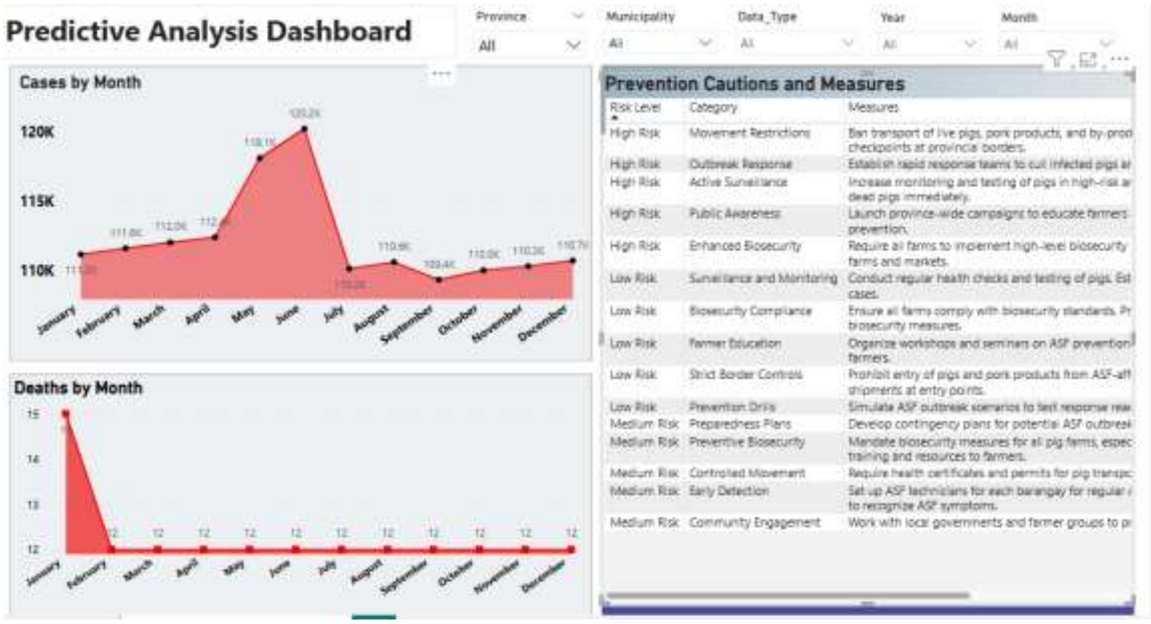

FIGURE 5. Predictive and prescriptive Analytics

Spatial Clustering Analysis of ASF Outbreaks

Figure 6 illustrates the DBSCAN clustering results for African Swine Fever (ASF) outbreak locations. Blue markers denote high-density outbreak clusters, while red markers identify isolated noise points that failed to meet the spatial density threshold. This visual differentiation is critical for epidemiological analysis, as it highlights severe transmission hotspots requiring immediate containment versus sporadic occurrences that pose a lower systemic threat.

FIGURE 6. DBSCAN algorithm spatial visualization

ISO/IEC 25010 System Evaluation

Table 1. Style Summary of ISO/IEC 25010 System Evaluation

ISO 25010 Characteristic	Overall User Perception	Sub-characteristic & Stakeholder Feedback
Functional Suitability	**Acceptable**	High consensus across all groups. The system effectively meets expected requirements. IT professionals rated *Functional*

		Completeness slightly lower than other groups, though still within acceptable margins.
Performance Efficiency	**Acceptable**	Users perceived response times and resource utilization as acceptable.
Compatibility	**Acceptable**	Strong agreement among all respondent groups that the system (*Co-existence*) operates effectively alongside other applications in shared environments without interference.
Interaction Capability (Usability)	**Acceptable**	ASF professionals and Policymakers reported high satisfaction. However, IT professionals rated *Learnability* (3.35) and *User Interface Aesthetics* (3.38) as only Moderately Acceptable, indicating a steeper learning curve and design flaws.
Reliability	**Acceptable**	Generally viewed as stable and fault-tolerant. IT professionals, however, rated *Availability* as Moderately Acceptable (3.46), hinting at perceived periodic downtimes.
Security	**Acceptable**	Users trust the system's confidentiality, integrity, and accountability mechanisms. IT professionals rated *Confidentiality* slightly lower (3.85) than other groups.
Maintainability	**Acceptable**	High ratings across *Modularity*, *Reusability*, and *Testability*. The system's underlying architecture is perceived as highly adaptable and well-structured for future updates.

Table 1 reveals a fundamental dichotomy between user perception and technical reality. While end-user particularly ASF professionals and policymakers reported high satisfaction with the system's functionality, interface, and perceived stability, objective technical audits exposed critical backend deficiencies.

CONCLUSION

This study concludes that the developed Decision Support System (DSS) effectively translates complex epidemiological data into proactive African Swine Fever (ASF) management strategies. While previous research primarily identified spatial outbreak bases (Mission & Rubio, 2024), this current iteration successfully implements an integrated framework that pairs DBSCAN-driven hotspot identification with Random Forest Regressor localized forecasting. This evolution provides stakeholders with actionable, data-driven interventions, such as preemptive quarantines and optimized resource allocation, to mitigate ASF outbreaks more effectively.

Regarding software quality under the ISO/IEC 25010 framework, a distinct dichotomy emerged between end-user perception and empirical technical reality. While ASF professionals and policymakers reported high satisfaction across all functional metrics, critical evaluations from IT professionals highlighted areas for technical remediation. Consequently, while the DSS represents a significant functional advancement over prior spatial models, its underlying architecture requires further optimization and cybersecurity hardening to ensure long-term viability prior to national-level deployment.

ACKNOWLEDGEMENTS

This author would like to thank the support of Commission on Higher Education SIKAP Grant-NCR, University of the East, Bureau of Animal Industry, WAHIS, and University of Antique.

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