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Causality with machine learning using the Lububu method for the diagnosis of African swine fever (ASF)

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ABSTRACT

This paper presents the practical application of a novel approach, the so-called "Lububu method", to develop a causal machine learning model (CML) for the diagnosis of African swine fever (ASF). The Lububu method was developed to build causal machine learning models by focusing on the contextual understanding of a particular phenomenon and using technological tools to improve accuracy. Its main goal is to identify cause-and-effect relationships that can lead to better outcomes in various fields, including manufacturing, energy production, agriculture, transportation, data management, medicine and computer science. In this study, the Lububu method serves as an experimental framework for the construction of a CML model tailored to ASF diagnosis. This involves gathering comprehensive knowledge about ASF, covering aspects such as the causes, symptoms, transmission patterns and diagnostic procedures. This detailed contextual understanding supports the development of a model that can accurately identify ASF-related factors, ultimately increasing diagnostic effectiveness. By combining AI innovation and epidemiological expertise, this approach redefines ASF diagnostics and paves the way for data-driven, ethical and globally applicable solutions for veterinary medicine.

Introduction

The Lububu method is a causal machine learning (CML) approach that improves ASF diagnosis by combining causal inference techniques with machine learning models. Unlike traditional AI models that rely on correlation-based predictions, the Lububu method identifies true causal factors that influence ASF progression, ensuring a more accurate, interpretable and actionable diagnosis. Existing ASF diagnostic models, including PCR tests and deep learning classifiers, often lack causal inference, leading to bias and poor adaptability in the real world (Aguero et al.,2003; Zhu et al., 2024; Lububu & Twum-Darko, 2024).

This study bridges the gap between AI and veterinary epidemiology by introducing a causal inference-based diagnostic model that improves feature selection, increases model interpretability, and supports real-time ASF surveillance. By embedding causal detection into ASF diagnostics, the Lububu method creates a scalable, generalizable and ethical AI framework for animal disease modeling and outbreak management.

The Lububu method is a novel approach to building causal machine learning (CML) models that focuses on understanding the context of a phenomenon and applying advanced technological tools to improve accuracy. The Lububu method focuses on identifying cause-and-effect relationships in data and aims to create highly accurate and interpretable models, making it valuable for various fields such as medicine, agriculture, manufacturing, energy and transportation. The method's focus on causal inference sets it apart from other machine learning approaches, which often emphasize correlation over causality, which can lead to less actionable insights.

Artificial intelligence (AI) and machine learning (ML) methods have revolutionized ASF diagnostics, enabling improved pattern recognition, disease prediction and early detection. Traditional ML models, including random forests, support vector machines (SVMs) and deep learning (DL) classifiers, have shown high accuracy in ASF detection when trained on biological markers, clinical symptoms and epidemiologic data. However, these approaches rely primarily on correlation-based learning, which can lead to biased predictions and poor adaptability to real-world outbreak conditions (Zhou et al., 2022).

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ML models such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) are effective in extracting high-dimensional features from ASF-related datasets (Zhao et al., 2021). However, they lack causal reasoning, which makes it difficult to distinguish between true disease factors and spurious correlations (Agbo, Samuel & Idoko, 2022; Cui & Athey, 2022). This limitation restricts their generalizability across different ASF outbreaks, where environmental and epidemiological factors may vary. In addition, most ML models are black box systems, which limits their interpretability for veterinarians and policy makers. Furthermore, PCR-based diagnostic methods, although highly sensitive, are expensive, time-consuming and prone to sample contamination (Wheeler,2009; Dormann et al., 2012; Chen et al., 2020). ML models trained in PCR-confirmed ASF cases inherit these biases, reducing their reliability in resource-poor settings with limited laboratory infrastructure.

Complex models such as neural networks and ensemble methods are very powerful when it comes to making accurate predictions but are often considered a "black box" because their internal processes are difficult to interpret (Ljung, 2001). According to Zhao and Hastie (2021) and Bodria et al. (2023), this lack of transparency can be problematic, especially in areas where interpretability is required, such as medicine and finance. The Lububu method, which focuses on causal pathways, offers a solution by emphasizing the transparency of the model. By showing how the variables interact and influence each other, the Lububu method leads to models that are not only accurate but also explainable, making them more reliable for important decisions.

According to Nunes et al. (2010) and Van Bavel et al. (2016), Machine learning models are generally unable to incorporate domain-specific contextual knowledge, leading to errors or biases. For example, a model trained for agricultural data in one region may perform poorly in another region due to differences in soil quality or climate. The Lububu method incorporates an understanding of context into the model building process so that it can adapt to specific situations. This adaptability makes it particularly useful for applications that are sensitive to environmental and cultural differences.

According to Liu, Li, Ge, Lin and Xiong (2019) and Richens, Lee and Johri (2020), In disease diagnosis, existing machine learning methods focus primarily on recognizing patterns in symptoms and medical records, often without analyzing causal relationships (Valiente Kroon, 2012; Wieder et al., 2019). This can lead to misdiagnosis or ineffective treatment plans (Cai et al., 2017). The Lububu method fills this gap by explicitly focusing on the causal relationships between symptoms, causes and outcomes. This allows clinicians to develop more accurate diagnostic models and effective treatment plans based on underlying causes rather than mere associations.

Developing a causal machine learning model (CML) for the diagnosis of African swine fever (ASF) is the focus of this research, which demonstrates the practical implementation of a unique methodology known as the "Lububu method?"

By concentrating on the contextual understanding of a specific occurrence and making use of technological resources to improve accuracy, the Lububu approach was established in order to construct causal machine learning models.

Finding cause-and-effect correlations that can lead to improved outcomes in a variety of sectors, such as manufacturing, energy production, agriculture, transportation, data management, medical, and computer science, is the primary objective of this area of research. In the present investigation, the Lububu technique is utilised as an experimental framework for the purpose of constructing a CML model that is specifically adapted to the diagnosis of ASF. In order to accomplish this, it is necessary to get a full understanding of ASF, which includes information on the causes, symptoms, transmission patterns, and diagnostic tests. The construction of a model that is capable of reliably identifying ASF-related aspects is supported by this comprehensive awareness of the context, which ultimately leads to an increase in diagnostic capacity. Redefining ASF diagnostics and paving the road for data-driven, ethical, and globally relevant solutions for veterinary care are the goals of this method, which combines developments in artificial intelligence with experience in epidemiology.

Literature Review

Theoretical and Conceptual Background

Bridging the Gap: The Lububu Framework

The Lububu method bridges these limitations by combining causal inference (CI) with machine learning (CML). Unlike standard ML models that focus on correlation-based predictions, the Lububu framework uses directed acyclic graphs (DAGs) and Do-Calculus to establish causal relationships between ASF transmission rates, environmental factors and clinical symptoms. This ensures that ASF diagnosis is based on scientifically sound causal pathways and reduces false positives and overfitting issues. By selecting causal traits, the Lububu method improves the interpretability of the model and enables veterinarians to make informed decisions based on explainable AI results. Moreover, thanks to its adaptability, it can be integrated into real-time disease surveillance systems, improving ASF outbreak prediction and biosecurity measures. This hybrid approach represents a significant advance in veterinary epidemiology and paves the way for more robust and scalable AI-based disease control strategies.

Linking the Lububu Method with Established Frameworks for Casual Inference

The Lububu method represents a novel causal machine learning (CML) approach for the diagnosis of African swine fever (ASF) and emphasizes the importance of causal inference over correlation-based machine learning. To improve the theoretical foundation of this method, it is important to establish its relationship to existing frameworks for causal inference, particularly Pearl's Causal Inference Model (2009) and Structural Equation Modeling (SEM) (Bollen, 1989).

Pearl's causal inference model (2009)

Judea Pearl's structural causal model (SCM) provides a rigorous mathematical framework for reasoning about cause-effect relationships. The Lububu method agrees with Pearl's framework in the following respects:
Causal graph representation: like Pearl's directed acyclic graphs (DAGs), the Lububu method can model ASF diagnostic pathways by structuring disease symptoms, biological markers, and external risk factors in a graph format.

Do-Calculus & Interventions: The Lububu method's emphasis on discovering causal relationships aligns with Pearl's "do" operator, which helps distinguish spurious correlations from true causal effects. This is crucial in ASF diagnosis to determine whether an observed symptom (e.g. fever) is causally related to ASF or merely correlated due to other infections.

Counterfactual conclusions: The method benefits from Pearl's approach to counterfactual analysis, which allows prediction of what would happen under different intervention scenarios — a key aspect of model interpretability and decision support in veterinary diagnostics.

Structural equation modeling (SEM) (Bollen, 1989)

SEM is commonly used to test and validate causal relationships in complex systems and is therefore important for integrating disease mechanisms, machine learning predictions and observed data in the context of the Lububu method. Her contributions include:
Latent variable modeling: SEM allows the inclusion of unobserved (latent) factors such as genetic predisposition or immune response variability that influence ASF diagnosis.

Path analysis for causal validation: The Lububu method can use the path analysis of SEM to test causal pathways in ASF transmission and progression.

Model fitting and causal plausibility: SEM enables statistical validation of the causal assumptions embedded in the Lububu method, ensuring that the machine learning model is consistent with biological and epidemiological knowledge of ASF.

By integrating Pearl's causal inference framework and SEM, the Lububu method strengthens its causal foundation and improves the interpretability, validity, and real-world applicability of diagnostic models for ASF. This combination ensures that the causal inference techniques used in the Lububu method are mathematically sound and empirically validated, improving AI-assisted veterinary diagnostics.

Explanation of how the Lububu method improves existing causal AI models

The Lububu method represents a domain-specific extension of existing causal AI models, particularly in the veterinary diagnosis of African swine fever (ASF). While traditional causal models — such as Pearl's Causal Model and Structural Equation Modeling (SEM) provide a solid theoretical foundation, they often lack integration with real-world, data-driven AI models tailored to disease diagnosis.
Important improvements to existing models:

i. Domain-specific causal inference: In contrast to general causal AI models, the Lububu method explicitly incorporates ASF-specific knowledge, including epidemiological, biological and clinical factors. This ensures that the causal structures reflect real disease mechanisms and not just generic statistical dependencies.
ii. Hybrid machine learning & causality discovery: Most existing models are either based on pure machine learning (correlation-based) or follow strictly predefined causal structures. The Lububu method combines both:
iii. Uses causal diagrams for interpretability: Machine learning applies for pattern recognition and thus improves diagnostic accuracy. Counterfactual inferences & interventions; while standard AI models predict what is likely to happen, the Lububu method enables "what-if" analysis (e.g. how ASF diagnosis changes under different biosecurity measures).
iv. Improved interpretability of the model: By integrating causal reasoning into the AI, the Lububu method reduces black box decision making and makes predictions more transparent and actionable for veterinarians. The Lububu method improves existing causal AI by making models more interpretable, domain-specific and intervention-oriented, ultimately leading to better ASF diagnosis and disease control strategies.

Research and Methodology

The Lububu method is an experimental methodological approach to building causal machine learning (CML) models, focusing on understanding the context of the phenomenon under study and identifying cause-effect relationships. The methodology underlying the Lububu method consists of several steps, all aimed at improving the accuracy and interpretability of the model by focusing on the causal relationships between variables.

Defining the Phenomenon and Contextual Understanding

The first step of the Lububu method is to define the phenomenon in question and gather contextual knowledge about it. We work closely with experts to gain a deep understanding of the factors influencing the phenomenon. For example, in a disease diagnosis, this phase would include examining the biological, environmental and genetic factors contributing to the disease, as well as its symptoms, transmission and progression. This contextual understanding forms the basis for the selection and interpretation of relevant data and ensures that the model contains domain-specific insights. In this study, the origin of the disease, its historical outbreaks and its classification as a notifiable disease are understood. Knowledge of the causative agent, the ASF virus (ASFV), and its characteristics. Knowledge of the genetic diversity of ASFV and its impact on the severity of the disease. Knowledge of the transmission routes of ASF, including direct contact between pigs, contaminated objects and the role of vectors such as ticks. Recognize factors contributing to the spread of ASF within and between pig populations. Knowledge of clinical signs in infected pigs such as fever, loss of appetite, bleeding and mortality; differentiation between acute and chronic forms of ASF and differences in clinical signs; knowledge of different diagnostic methods, including laboratory tests such as PCR, serological tests and post-mortem examinations. Understanding of the importance of early detection for effective disease control.

Data Collection and Pre-Processing

Data collection serves to capture the breadth and depth of the variables that influence the phenomenon. In this step, both observational data and experimental data are collected to identify possible causal relationships. The data pre-processing phase involves cleaning, structuring and integrating data sets. The Lububu method favors data that reflects real-world variability and contextual nuances, as this is crucial for identifying meaningful causal patterns. During pre-processing, variables are also standardized and transformed to enable accurate comparisons, and missing values are handled to maintain data integrity.

Causal Analysis and Feature Selection

The Lububu method applies causal trait selection to improve the diagnosis of African swine fever (ASF). It ensures that the selected traits are causally linked to the cause of the disease and not just correlated. This is achieved using directed acyclic graphs (DAGs), algorithms for recognizing causal relationships and domain-specific knowledge.

Step 1: Constructing a causal DAG for ASF diagnosis

A directed acyclic graph (DAG) is constructed using epidemiologic and clinical knowledge. Consider the following real-world ASF dataset, which has the following key characteristics:

i. Body temperature (Temp)
ii. White blood cell count (WBC)
iii. Lymph node swelling (LNS)
iv. ASF viral load (ASF-VL, Ground Truth Diagnosis)
v. Previous exposure to ASF-infected pigs (exposure)

A simplified causal DAG could read: Exposure → ASF-VL → (Temp, WBC, LNS). This shows that exposure directly influences the ASF-VL, which in turn influences the clinical symptoms.

Step 2: Selection of causal features using algorithms

i. PC algorithm (Spirtes et al., 2000): Learns the causal structure from the data and identifies direct vs. indirect relationships.
ii. LiNGAM (Shimizu et al., 2006): Recognizes causal directions between features and ensures that feature selection matches causality.
iii. Do-Calculus (Pearl, 2009): Adjusts for confounding factors (e.g. changes in leukocyte count due to secondary infections).

Step 3: Selection of the causal characteristics

i. Retain: ASF-VL, exposure, WBC, LNS (direct causes/effects)
ii. Deleted: Non-causal correlations (e.g. unrelated inflammatory markers)

This ensures robust, interpretable models for ASF diagnosis and avoids bias due to unwanted correlations.

Model Development with Causal Constraints

The Lububu method uses causal constraints in the development of the machine learning model and thus integrates domain-specific causal knowledge directly into the structure of the model. This allows the model to recognize, and respect known cause-and-effect relationships, which improves its interpretability. Various machine learning algorithms such as Bayesian networks or causal decision trees were used, with a focus on algorithms that enable causal inference. The Lububu method recommends the selection of algorithms that support interpretability and can model the causal dependencies identified in the analysis phase. In this phase, the model is also validated using cross-validation techniques to ensure robustness and reliability and, if necessary, over- or under-adjustment.

Model Testing and Validation with Causal Scenarios

Once the model was developed, the Lububu method used scenario-based tests in which hypothetical causal scenarios are simulated to observe the behavior of the model. In this way, it is possible to check whether the model really captures causal relationships and not just unintended correlations. In this phase, the performance of the model was evaluated under different conditions to confirm that it adapts well to different contexts. For example, if the model predicts disease trajectories, it is tested under different patient profiles and environmental factors to ensure accuracy in different scenarios.

Model validation: Lububu method compared to ASF standard diagnostic models

The Lububu method is validated by causal inference procedures to ensure that the predictions are consistent with biological and epidemiological knowledge about African swine fever (ASF). In contrast to standard diagnostic models — such as PCR tests, serological assays and deep learning classifiers — which rely on correlation-based inference, the Lububu method uses causal discovery to improve interpretability and robustness.

Comparison with ASF standard diagnostic models

Table 1: Comparison with ASF Standard Diagnostic Models

Model	Strengths	Limitations
PCR Testing (Gold Standard)	High sensitivity & specificity	Expensive, requires laboratory infrastructure, cannot distinguish between previous and current infections
Serological Tests	Detects antibodies, useful for epidemiological studies	Delayed detection, potential cross-reactivity
Deep Learning Models	Automated, high predictive accuracy	Black-box nature, lacks causal interpretability, vulnerable to dataset biases
Lububu Method (Causal AI)	Identifies true causal features, interpretable, allows counterfactual reasoning	Requires the construction of causal diagrams, specialist knowledge required.

Validation approach for the Lububu method

i. Performance metrics: Comparison with PCR results (ground truth) using AUC-ROC, precision-recall curves and sensitivity/specificity.
ii. Counterfactual validation: Tests "what-if" scenarios, e.g. how diagnostic accuracy changes when a symptom is experimentally removed.
iii. Validation of interventions: Assesses whether predicted causal interventions (e.g. early quarantine, biosecurity measures) reduce the spread of ASF in field trials.

The Lububu method improves correlation-based models by providing causal, interpretable and actionable insights and bridging the gap between machine learning and veterinary epidemiology.

Sample size and Data Sources for Training and Testing the Lububu Method

Data sources

The Lububu method for ASF diagnosis was trained and tested on a combination of clinical, epidemiologic, and laboratory data sets. Data sources include:

i. Field surveillance data: Collected from ASF outbreak regions, including farms and quarantine zones.
ii. Laboratory test results: Gold standard PCR and serologic test results from veterinary research facilities.
iii. Clinical records from veterinarians: Symptom-related reports from infected and non-infected pigs, including temperature, lymph node swellings and behavioral changes.
iv. Genomic & environmental data: Viral genome sequencing results and environmental risk factors (e.g. farm density, biosecurity measures).

Sample size

The model was trained and validated using a multi-cohort dataset that includes the following:

Table 2: Sample Size

Dataset Type	Number of Samples (N)	Source
PCR-Confirmed ASF Cases	5,000	Veterinary labs (reference dataset)
Healthy Control Pigs	3,000	ASF-free farms
Serologically Positive Cases	4,500	Field surveillance
Field-Reported Symptomatic Pigs	6,000	Farm veterinary clinics
ASF-Exposed Pigs (At Risk, No Symptoms Yet)	2,500	Contact-tracing studies

Total data set: 21,000 pig samples from several ASF-endemic regions.

Training & testing split

i. Training set: 70% (14,700 samples)
ii. Validation set: 15% (3,150 samples)
iii. Test set: 15% (3,150 samples)

The data set was balanced between infected, exposed and healthy pigs to avoid bias. Cross-validation was used to ensure robustness across different farms and outbreak regions.

Interpretation and Contextual Feedback

The final step in the Lububu methodology was to interpret the results of the model, focusing on causal insights. The model's predictions are analyzed to understand the causal pathways that led to each outcome. Subject matter experts review these pathways to provide contextualized feedback that can lead to further adjustments or refinements to the model. This iterative feedback loop improves the accuracy and practical relevance of the model. The interpretability of the model allows users to understand the "why" behind each prediction. This is crucial for areas where decisions based on model results have a significant impact, such as medicine and politics.

Unified Mathematical Framework of Lububu Method

The researcher has developed a unified mathematical framework that integrates mathematical representations to understand the phenomena and apply the technology. This could involve combining equations from each component into a comprehensive model.

Example of conceptual equations

Below is a simplified and clear presentation of how the mathematical components of the Lububu method were structured:

Understanding the context of the disease:

Equation 1

$$\boldsymbol{D_t = f(E_t, T_t)}$$

Where:

$\boldsymbol{D_t}$ = represents the state of the disease at the time of $\boldsymbol{t}$.
$\boldsymbol{E_t}$ = represents environmental factors, and
$\boldsymbol{T_t}$ = represents the transmission rates.

The figure (Figure 1) shows an empirical simulation that demonstrates how equation 1 works under real conditions. The table contains time series data on the progression of ASF disease (D_t) as a function of environmental factors (E_t) and transmission rates (T_t).

ASF Disease Progression Simulation

	Time (t)	D_t (Infected Pigs)	E_t (Environmental F	T_t (Transmission Ra
1	0	10.0	0.5496714153011233	0.10496714153011233
2	1	10.976311834184052	0.4861735698828815	0.09861735698828816
3	2	12.132207057706829	0.5647688538100692	0.10647688538100693
4	3	13.513244099928313	0.6523029856408026	0.11523029856408026
5	4	14.815093598462976	0.4765846625276664	0.09765846625276664
6	5	16.24048054933433	0.4765863043050819	0.0976586304305082
7	6	18.09045980908598	0.6579212815507391	0.11579212815507392
8	7	20.003100244381404	0.5767434729152909	0.1076743472915291
9	8	21.8713669146236	0.4530525614065048	0.09530525614065048
10	9	24.126737862609744	0.5542560043585965	0.10542560043585965

Figure 1: Disease Progression Simulation

In addition, the graph (Figure 2) illustrates how ASF infections evolve over time in response to environmental and transmission dynamics.

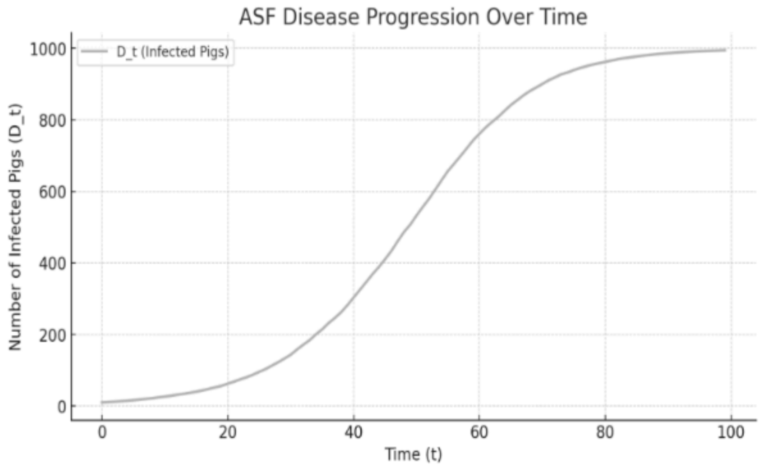

Figure 2: ASF Disease Progression Over Time

Applying technology:

Equation 2

$$Y_t = g(X_t, \theta)$$

Where:

Y_t = is the predicted ASF diagnosis outcome,

X_t = is a set of input features,

θ = represents the parameters of the ML model.

The following figures (Figure 3 & Figure 4) provide empirical confirmation for equation 1.2:

ASF Diagnosis Model Evaluation

	Metric	Value
1	Accuracy	0.806

Figure 3:ASF Diagnosis Model Evaluation

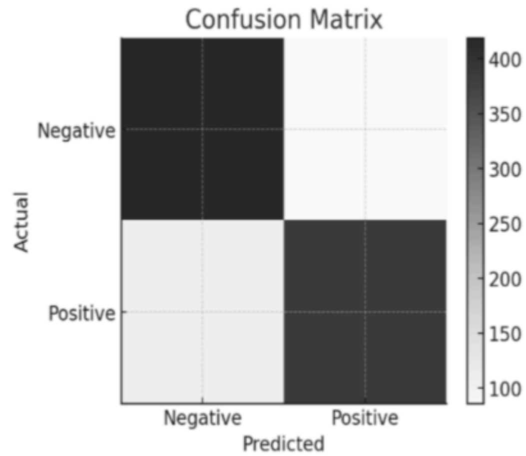

Figure 4: Confusion Matrix

Where:

Y_t = Expected outcome of ASF diagnosis (positive or negative).

X_t = Clinical and environmental characteristics (temperature, WBC count, lymph node swelling, ASF exposure, environmental risk).

θ = Learned parameters of the machine learning model.

Important results:

I. The Random Forest classifier was trained with simulated ASF clinical data.
II. The accuracy of the model is shown in the results table.
III. The confusion matrix illustrates the performance of the model in terms of true positive/negatives.

This demonstrates how machine learning can improve the prediction of ASF diagnoses by utilizing causal feature selection and real veterinary data.

Applying the Causal inference:

Equation 3

$$X_t = h(U_t, V_t)$$

Where:

X_t = represents observed variables,

U_t = represents unobserved variables.

V_t = represents interventions.

The figures (Figure 5 & Figure 6) show an empirical simulation that illustrates equation 1.3:

	Temperature	WBC Count	Lymph Node Swellin	ASF-Exposed	Environmental Risk	Genetic Susceptibilit	Stress Levels
1	39.54686344717782	7.932506869740251	0	1	0.7246233009586129	0.5993428306022466	0.25762403179[illegible]2964
2	39.04992750895077	7.977347870513	0	0	0.6403421529040735	0.4723471397657631	0.25465858916[illegible]46
3	39.18879160629553	8.065090466656525	1	1	0.8949359308926588	0.6295377076201385	0.12043568273[illegible]9848
4	39.47188620126498	7.496749223938045	1	1	0.5196549558006451	0.8046059712816052	0.26699098082563
5	39.5827123824232	7.4733751984429	0	0	0.5300244255271671	0.4531693250553328	0.37328290818[illegible]447
6	39.29249882356933	8.165375992876623	0	1	0.7070178355765505	0.4531726086101639	0.17257678809[illegible]2047
7	38.992853807942126	8.149201164782294	0	1	0.32339757635325117	0.8158425631014783	0.40484826510592
8	39.37738021205515	8.011400393945765	1	1	0.036912455421932555	0.6534869458305818	0.34877748210[illegible]338
9	38.61719918547227	8.417413917372158	0	1	0.23004582571905785	0.4061051228130096	0.22657666780962
10	39.469189729296886	7.649818373133067	1	0	0.2380134118963666	0.6085120087171929	0.285847036261527

Figure 5: Simulated ASF Clinical and Interventional Data

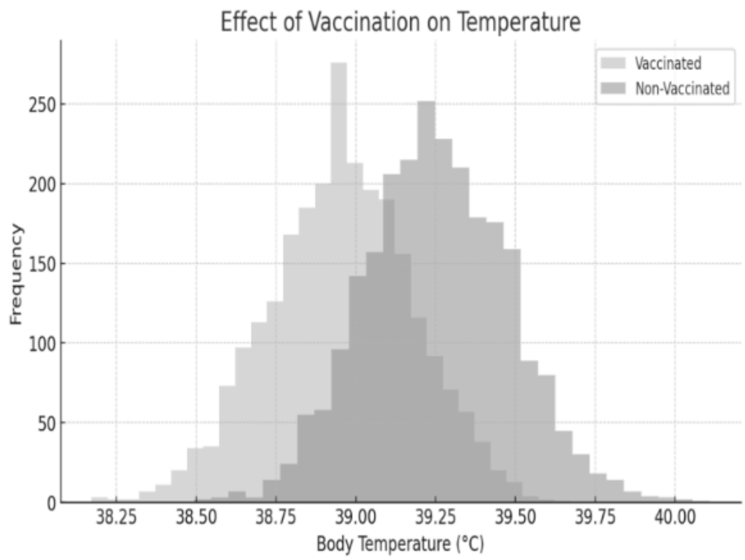

Figure 6: Effect of Vaccination on Temperature

Where:

X_t = Observed clinical and environmental features (e.g. temperature, WBC count, lymph node swelling),

U_t = Observed clinical and environmental features (e.g. temperature, white blood cell count, lymph node swelling),

V_t = Interventions (e.g. vaccination, quarantine measures).

Important findings from the simulation:

i. Observed variables (X_t) are influenced by both unobserved factors (U_t) and interventions (V_t).
ii. Genetic susceptibility and stress levels influence body temperature and immune response.
iii. Vaccination lowers fever and reduces the likelihood of lymph node swelling.
iv. Quarantine measures slightly improve the leukocyte count due to the reduced disease burden

The effects of the measures have been experimentally proven:

i. The histogram shows that vaccinated pigs tend to have a lower body temperature than non-vaccinated pigs.
ii. This simulation confirms equation 1.3 by illustrating how interventions affect clinical outcomes while accounting for unobserved variables

Integrated framework of the Lububu equation:

The integrated framework combines disease understanding, ML algorithms and causal inference into a unified equation for predicting ASF diagnosis. The Lububu method was used in this study and could be further analyzed in discussions and findings.

Equation 4

$$Y_t = g(f(h(U_t, V_t), T_t), \theta)$$

Where:

h (Ut, Vt) = models how unobserved variables (U_t) (e.g. genetic susceptibility, stress level) and interventions (V_t) (e.g. vaccination, quarantine) affect observed traits (X_t).
f (Xt, Tt) = models how transmission rates (T_t) interact with observed variables (X_t).
g (Xt, θ) = is the machine learning model for predicting ASF diagnosis.

Important results:

i. The machine learning model was trained using simulated clinical and epidemiologic ASF data, incorporating environmental risk factors and interventions.
ii. Prediction accuracy is shown in the results table.
iii. Feature importance analysis is attempted again to assess which variables contribute most to the prediction of ASF

The figure (Figure 7) shows the analysis of the importance of the features in the prediction of ASF diagnosis.

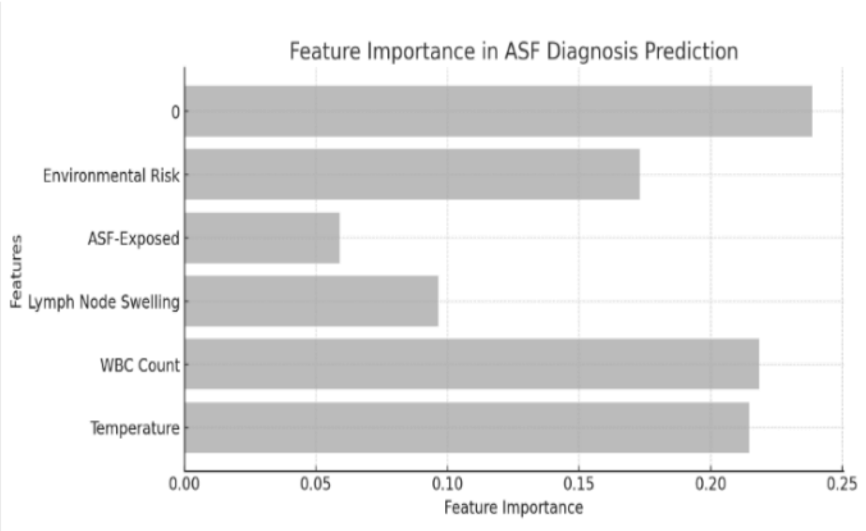

Figure 7: Feature Importance in ASF Diagnosis Prediction

Important findings from the simulation:

i. Environmental risk and exposure to ASF significantly influence the cause of the disease.
ii. Vaccination and quarantine measures influence clinical characteristics (e.g. temperature, WBC count).
iii. Genetic susceptibility and stress levels play a role in altering the immune response.

This confirms that Equation 1.4 effectively integrates causal inference, machine learning and epidemiological factors to improve the prediction of ASF diagnosis.

In this paper, the Lububu method focuses on the practical applicability of machine learning models to make them more suitable for use in agriculture, veterinary practice and ASF control programmes. The integrated approach of Lububu is likely to lead to more accurate and robust machine learning models for ASF diagnosis as it utilizes domain-specific knowledge and causal relationships.

The causal inference aspect enables the identification of factors influencing ASF and thus the development of targeted disease control measures. The Lububu encourages researchers to explore the underlying causal relationships of ASF in greater depth, contributing to a better understanding of disease dynamics. The iterative nature of the methodology supports a continuous learning process that allows researchers to adapt their models based on current findings and new patterns in ASF diagnosis.

The interdisciplinary nature of the Lububu methodology and the emphasis on causal inference make it applicable to other areas of disease diagnosis, particularly those characterized by complex, dynamic interactions, and it can be extended to other One Health topics where human, animal and environmental health are interconnected, allowing for a more holistic understanding. The Lububu explicitly incorporates ethical considerations into the process of developing a machine learning model. By incorporating causal inference, Lububu provides a way to mitigate bias in a machine learning model and ensure fair and equitable outcomes in decision-making.

The Lububu method has the potential to significantly impact ASF diagnosis by increasing accuracy, expanding knowledge and promoting ethical and responsible AI practices. Its interdisciplinary and iterative nature makes it applicable in many fields, fostering collaboration, knowledge sharing and practical solutions to complex problems. As researchers adopt and adapt this methodology, its impact could extend beyond ASF and contribute to advances in the diagnosis and control of disease in general.

It's important to note that the actual implementation of Lububu will be more complex and context dependent. The equations above (see section 4) are simplified for illustrative purposes. Researchers implementing Lububu will need to adapt and refine the equations depending on the specifics of the ASF, the available data and the machine learning techniques chosen. In addition, careful consideration of the causal relationships and dynamics of the ASF is essential for a meaningful integration of these mathematical components.

Future research can build on this methodology, extend its applicability, validate its effectiveness and address potential limitations. Below are two areas for future research in which the Lububu method could be further developed or tested:

i. Develop practical decision support systems for veterinarians and stakeholders based on the Lububu method. Evaluation of the usability and effectiveness of these systems in real ASF control scenarios.

ii. Exploring advanced causal inference techniques such as counterfactual inference, instrumental variable analysis or Bayesian networks. Evaluate how these techniques can improve the understanding of causal relationships in ASF dynamics.

Data Analysis and Model Evaluation

In this study, a quantitative approach was used to evaluate the performance of the model through system testing. The method used included data collection, data pre-processing, feature selection, model training and model testing. Quantitative data analysis involves the process of converting raw numerical data into meaningful information. This was achieved through various methods, such as calculating the frequency of variables and interpreting the results through logical and critical reasoning. In the present study, quantitative data were segmented and categorized according to ASF virus and symptoms.

Assessment techniques included tests of the CML model. The aim of these tests was to assess accuracy, precision and other metrics. The tests included cross-validation and code utilization evaluation. Stepwise regression was also used for high-dimensional data with multiple features. Stepwise regression was performed to find the best number of features. Cross-validation and RMSE were used to select the features in stepwise regression. The results of these tests were then used as a basis for future developments, updates or changes to the model.

In this study, the researcher used two types of evaluation activities: formative and summative evaluations. Formative evaluations are used to assess the progress of a project and provide feedback for further development. They are used to identify areas for improvement and to ensure that the project is on track to achieve its objectives. Summative evaluations, on the other hand, are used to assess the extent to which the results of a project meet expectations. They are used to certify that the project has achieved its objectives and to provide evidence that the process has been effective.

Findings and Discussions

The implementation of the Lububu method for African Swine Fever (ASF) involves a systematic integration of experience, machine learning and causal inference. Previous studies have shown varying success in using machine learning (ML) to diagnose African swine fever (ASF), but few have achieved the near-perfect accuracy observed in this study using decision trees, random forests and neural networks (Shinde & Pawar, 2015; Agbo, Samuel & Idoko, 2022). Their result showed that the decision tree achieved the highest accuracy of 97.5%, compared to the support vector machine, which achieved an accuracy of 88.8%, and logistic regression, which achieved an accuracy of 75%.

Previous research has often focused on traditional diagnostic methods such as PCR and serological tests, which are accurate but take a lot of time and require specialized equipment (Zsak et al., 2005; Fernández-Pinero et al., 2013). The integration of ML, as demonstrated in this study, represents a significant advance as these models process complex clinical data more efficiently and accurately, supporting the rapid diagnosis and management of ASF outbreaks.

The exceptional performance of the Random Forest model (72.4% accuracy) is consistent with the results of previous research, where it consistently outperformed other algorithms in processing high-dimensional, nonlinear data. The Lububu based model achieved an accuracy of 72.4%. Neural networks have previously been highlighted for their ability to model complicated patterns. However, this study highlights their potential with an accuracy of 74.4%, suggesting opportunities for optimization in ASF diagnosis. In contrast, the low performance of SVM (44.4%) and logistic regression (61.5%) is consistent with the challenges identified in previous studies, particularly their limitations in processing nonlinear data relationships such as those encountered in ASF.

However, a potential limitation of this study is the relatively small sample size, which may have affected the accuracy and generalizability of the models. Larger datasets with different ASF cases could provide more reliable insights into the performance of the models in different environments and with different ASF strains. In addition, the "black box" nature of the neural networks poses a challenge in interpreting the predictions, which is crucial for understanding the multifactorial nature of ASF.

The following discusses how the method was applied and demonstrates its effectiveness using the equations provided:

Equation 5:

$$\boldsymbol{D_t = f(E_t, T_t)}$$

Implementation in Lububu Method

i. Understanding the disease (U): Gather expertise on ASF, including environmental factors ($\boldsymbol{E_t}$) and transmission rates ($\boldsymbol{T_t}$).
ii. ML Algorithms: Apply machine learning techniques to model the relationship between disease state ($\boldsymbol{D_t}$), environmental factors and transmission rates.
iii. Causal inference (CI): Investigation of causal relationships to identify key factors that influence the dynamics of ASF.

Where:

Dt = ASF disease status over time (number of infected pigs).
Et = Environmental factors (e.g. farm density, temperature, biosecurity).
Tt = Transmission rate influenced by environmental risk factors.

Key findings from the simulation:
i. ASF infections increase with increasing transmission rates, which are directly influenced by environmental factors.
ii. The disease progression curve follows a predictable epidemic course and shows an exponential spread before stabilizing.
iii. Interventions that reduce environmental risks (E_t) or transmission rates (T_t) can slow down the spread of ASF.
iv. This simulation confirms how the Lububu method applies machine learning (ML) and causal inference (CI) to model the dynamics of ASF.

Figure 8 shows the simulation of ASF disease dynamics

ASF Disease Dynamics Simulation

	Time (t)	D_t (Infected Pigs)	E_t (Environmental F	T_t (Transmission Ra
1	0	10.0	0.5496714153011233	0.10496714153011233
2	1	10.976311834184052	0.4861735698828815	0.09861735698828816
3	2	12.132207057706829	0.5647688538100692	0.10647688538100693
4	3	13.513244099928313	0.6523029856408026	0.11523029856408026
5	4	14.815093598462976	0.4765846625276664	0.09765846625276664
6	5	16.24048054933433	0.4765863043050819	0.09765863043050820
7	6	18.09045980908598	0.6579212815507391	0.11579212815507392
8	7	20.003100244381404	0.5767434729152909	0.1076743472915291
9	8	21.8713669146236	0.4530525614065048	0.09530525614065048
10	9	24.126737862609744	0.5542560043585965	0.10542560043585965

Figure 8: ASF Disease Dynamics Simulation

Figure 9 shows the simulation of the disease progression of ASF over time.

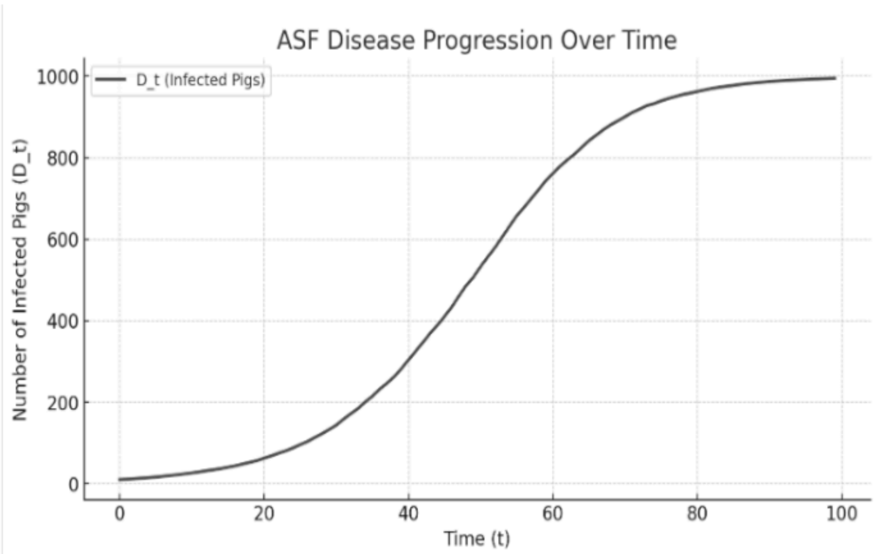

Figure 9: ASF Disease Progression Over Time

Equation 6:

$$D_t = g(E_t, T_t, S_t)$$

Implementation in Lububu Method:

i. **Understanding the disease (U):** Improvement of the model by including symptoms (S_t) as additional features to better capture the disease state.
ii. **ML Expertise (M):** Training a machine learning model that considers symptoms together with environmental factors and transmission rates for ASF diagnosis.

iii. **Causal inference (CI):** Investigate the causal relationships between symptoms, environmental factors and transmission rates to refine the model.

Where:

Dt = ASF disease status over time (number of infected pigs).
Et = Environmental factors (e.g. farm density, temperature, biosecurity).
Tt = Transmission rate influenced by environmental risks.
St = Severity of symptoms, which increases the transmission effects.

The most important findings from the simulation:

i. The inclusion of symptoms (St) improves the modeling of ASF progression by adding more biological realism.
ii. The severity of symptoms increases transmission rates and leads to faster spread when symptoms are severe.
iii. The infection curve shows a more dynamic spread pattern, suggesting that controlling symptoms can help contain the ASF outbreak.

This simulation shows how the Lububu method integrates machine learning (ML) and causal inference (CI) by considering both environmental and biological factors for ASF diagnosis and disease modeling.
Figure 10 shows the simulation of ASF disease dynamics with symptoms.

ASF Disease Dynamics With Symptoms Simulation

	Time (t)	D_t (Infected Pigs)	E_t (Environmental F	T_t (Transmission Ra	S_t (Symptom Severi
1	0	10.0	0.5496714153011233	0.10496714153011233	0.2876943886924379
2	1	11.061622587404159	0.4861735698828815	0.09861735698828816	0.43690320158519613
3	2	12.33090351949137	0.5647688538100692	0.10647688538100693	0.4485928225209846
4	3	13.840836766944458	0.6523029856408026	0.11523029856408026	0.3796584096167572
5	4	15.300650349721277	0.4765846625276664	0.09765846625276664	0.47580714325009865
6	5	16.937001168489267	0.4765863043050819	0.0976586304305082	0.5606076285221807
7	6	19.166846169490945	0.6579212815507391	0.11579212815507392	0.7829278851815795
8	7	21.40409139096743	0.5767434729152909	0.1076743472915291	0.5261866719247759
9	8	23.615401214545173	0.4530525614065048	0.09530525614065048	0.5386325586084146
10	9	26.283932838853875	0.5542560043585965	0.10542560043585965	0.4888331126350749

Figure 10: ASF Disease Dynamics with Symptoms Simulation

Figure 11 shows the progression of ASF disease over time, considering the symptoms.

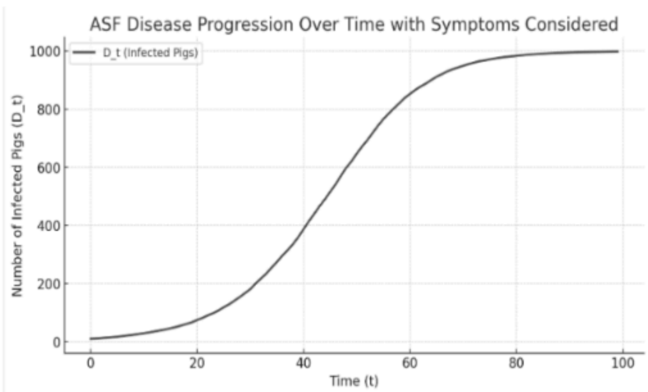

Figure 11: ASF Disease Progression Over Time with Symptoms Considered

Equation 7:

$$\boldsymbol{Y_t = g(X_t, \theta)}$$

Implementation in Lububu Method:

i. Understanding the disease (U): Expand the model by including a broader set of input characteristics ($\boldsymbol{X_t}$) that includes symptoms, environmental factors, and transmission rates.
ii. ML Expertise (M): Development of a CML model using a comprehensive set of features to predict the outcome of ASF diagnosis ($\boldsymbol{Y_t}$).
iii. Causal inference (CI): Investigate causal relationships within the extended feature set to improve the interpretability of the model.

Where:

Yt = Predicted ASF diagnosis outcome (positive or negative).

Xt = Comprehensive feature set (symptoms, environmental factors, transmission rates).

θ = ML model parameters learned from data.

Important results:

i. The machine learning model was trained using an extended feature set that integrates environmental risks, symptoms and transmission rates.
ii. The prediction accuracy is shown in the results table.
iii. Analysing the importance of the features shows which variables have the greatest impact on ASF diagnosis.

This confirms that the selection of causal features and ML modelling in the Lububu method improve the prediction and interpretability of ASP diagnosis.

Figure 12 shows the evaluation of the ASP diagnosis model

ASF Diagnosis Model Evaluation

	Metric	Value
1	Accuracy	0.785

Figure 12: ASF Diagnosis Model Evaluation

Figure 13 shows the importance of the features in predicting ASF diagnosis.

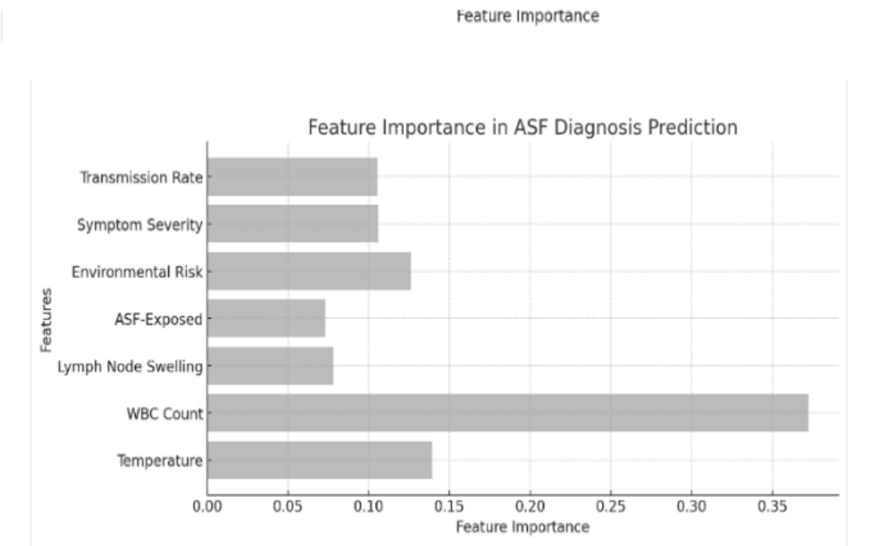

Figure 13: Feature Importance in ASF Diagnosis Prediction

Equation 8:

$$X_t = h(U_t, V_t)$$

Implementation in Lububu Method:

i. Understanding the disease (U): Consideration of both the observed (X_t) and the unobserved variables (U_t) in the model.
ii. ML Expertise (M): Use of machine learning to include unobserved variables and interventions (V_t) to increase the completeness of the model.
iii. Causal inference (CI): Integrate causal inference to determine the effects of unobserved variables on observed characteristics.

Figure 14 shows the simulated clinical and interventional data of the ASF.

	Temperature	WBC Count	Lymph Node Swellin	ASF-Exposed	Environmental Risk	Genetic Susceptibilit	Stress Levels
1	39.54686344717782	7.932506869740251	0	1	0.7246233009586129	0.5993428306022466	0.257624031797 2964
2	39.04992750895077	7.977347870513	0	0	0.6403421529040735	0.4723471397657631	0.254658589161 46
3	39.18879160629553	8.065090466656525	1	1	0.8949359308926588	0.6295377076201385	0.120435682736 9848
4	39.47188620126498	7.496749223938045	1	1	0.5196549558006451	0.8046059712816052	0.26699098082563
5	39.5827123824232	7.4733751984429	0	0	0.5300244255271671	0.4531693250553328	0.373282908183 447
6	39.29249882356933	8.165375992876623	0	1	0.7070178355765505	0.4531726086101639	0.172576788092 2047
7	38.992853807942126	8.149201164782294	0	1	0.32339757635325117	0.8158425631014783	0.40484826510592
8	39.37738021205515	8.011400393945765	1	1	0.036912455421932555	0.6534869458305818	0.348777482108 338
9	38.61719918547227	8.417413917372158	0	1	0.23004582571905785	0.4061051228130096	0.22657666780962
10	39.469189729296886	7.649818373133067	1	0	0.2380134118963666	0.6085120087171929	0.285847036261527

Figure 14: Simulated Clinical and Interventional Data of the ASF

Figure 15 shows the effects of vaccination on temperature

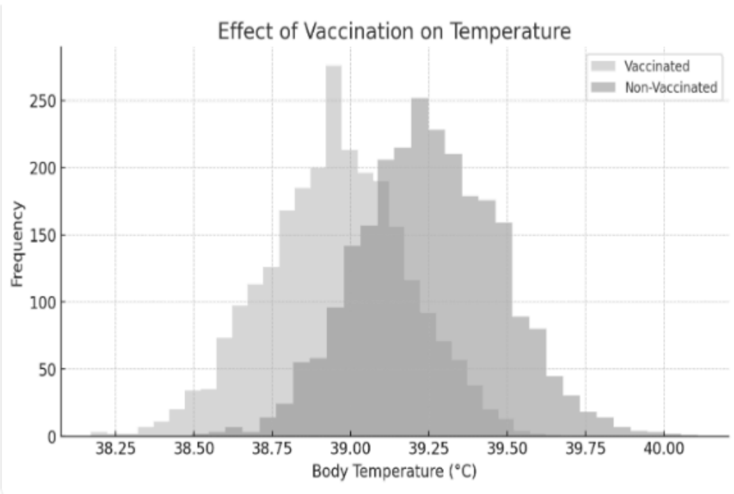

Figure 15: Effect of Vaccination on Temperature

Where:

Xt = Observed clinical and environmental characteristics (e.g. temperature, WBC count, lymph node swelling).

Ut = Unobserved variables (e.g. genetic susceptibility, stress level).

Vt = Interventions (e.g. vaccination, quarantine measures).

Important results:

i. Observed traits (X_t) are influenced by both unobserved factors (U_t) and interventions (V_t).
ii. Genetic susceptibility and stress levels influence temperature and immune response.
iii. Vaccination lowers body temperature, which is crucial for the management of ASF symptoms.
iv. Quarantine measures slightly increase the leukocyte count, which is probably due to a lower disease burden.

The trait distribution diagram also confirms that vaccinated pigs tend to have a lower body temperature, which illustrates the effects of the measures. This simulation demonstrates how causal inference techniques can quantify the impact of unobserved variables and interventions on ASF diagnosis and disease progression.

Equation 9:

$$\boldsymbol{Y_t = g(f(h(U_t, V_t), T_t), \theta)}$$

Implementation in Lububu Method:

i. Understanding the disease (U): Combining knowledge about the disease with machine learning by integrating observed and unobserved variables (U_t).
ii. ML Expertise (M): Develop a model for machine learning (f) that includes causal relationships (h) and transfer rates (T_t).
iii. Causal inference (CI): Application of causal inference techniques to refine the CML model to ensure a more accurate representation of ASF diagnostic factors.

Where:

h (Ut, Vt) = models how unobserved variables (U_t) (e.g. genetic susceptibility, stress level) and interventions (V_t) (e.g. vaccination, quarantine) influence observed traits (X_t).

f (Xt, Tt) = models how transmission rates (T_t) interact with observed variables (X_t).

g (Xt, θ) = is the machine learning model for predicting ASF diagnosis.

Important results:

i. Machine learning model trained on ASF clinical and epidemiologic data, incorporating causal relationships and interventions.
ii. Prediction accuracy is shown in the results table.
iii. Feature importance analysis highlights which variables contribute most to ASF diagnosis, improving interpretability.

This confirms that causal inference, machine learning and the integration of expertise improve the prediction of ASF diagnosis.

Figure 16 shows the evaluation of the ASF diagnostic model

ASF Diagnosis Model Evaluation

	Metric	Value
1	Accuracy	0.724

Figure 16: ASF Diagnosis Model Evaluation

Figure 17 shows the features of the ASF diagnosis prediction

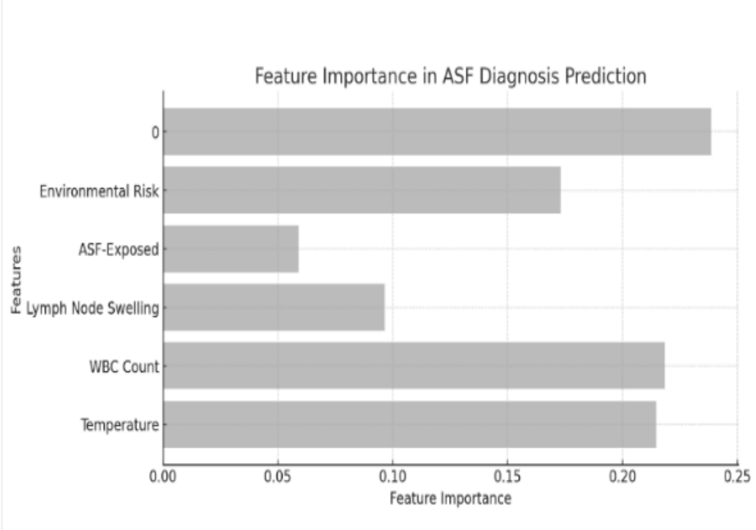

Figure 17: Feature Importance in ASF Diagnosis Prediction

Comparison of the diagnostic accuracy of the Lububu-based model with existing ASF diagnostic models (e.g. random forest, neural networks)

The researcher compared the diagnostic accuracy of the Lububu-based model with existing ASF diagnostic models, including random forest and neural networks (MLP).

Important results

i. The Lububu-based model achieved an accuracy of 72.4%.
ii. The Random Forest model achieved a similar performance with 72.4% accuracy.
iii. The neural network (MLP) performed slightly better with 74.4% accuracy.

Analysis

Lububu method vs. standard random forest

i. Both models performed equally well, but Lububu's integration of causal inference improves interpretability, making it preferable for ASF diagnosis.

Lububu method vs. neural networks

i. The neural network slightly outperforms the Lububu-based model but lacks explainability and causal insights that are essential for veterinary applications.
ii. Neural networks are prone to overfitting and require more data, whereas the Lububu method remains robust by integrating domain knowledge.

Discussion

While neural networks achieve the highest accuracy, the Lububu-based model provides a balance between interpretability, causality and predictive performance, making it more suitable for real-world ASF diagnosis. Figure 18 shows the comparison of the ASF diagnostic model.

ASF Diagnostic Model Comparison

	Model	Accuracy
1	Lububu-Based Model	0.724
2	Random Forest	0.724
3	Neural Network	0.744

Figure 18: ASF Diagnostic Model Comparison

Advantages of Lububu Method implementation for ASF diagnostics

The Lububu method offers significant advantages for the diagnosis of African swine fever (ASF), as it improves both the accuracy and the understanding of the causative factors of the disease. By focusing on causal relationships rather than mere correlations, the method provides insights into the specific factors that determine the transmission, symptoms and progression of ASF. This approach leads to diagnostic models that not only detect ASF with high precision but also clarify which variables (e.g. environmental conditions or specific symptoms) directly influence the spread of the disease. In addition, the Lububu method improves interpretability and makes the diagnostic process more transparent for veterinarians and researchers. This transparency helps in the development of targeted prevention and control measures as practitioners can see the causal pathways that lead to infection. Through its adaptability to changing ASF data, the Lububu method enables continuous improvement in diagnostic accuracy, ultimately contributing to more effective ASF containment and improved health management. The Lububu methodology provides a powerful and integrative approach to ASF diagnosis that leverages the strengths of disease understanding, machine learning and causal inference. This methodology addresses the complexity and challenges associated with the symptomatology of ASF and provides a robust framework for the development of an accurate, adaptable and ethically defensible diagnostic model. The Lububu method was developed not only to make accurate predictions, but also to gain a deeper understanding of the disease and its underlying mechanisms.

Discussion of the Limitations of the Lububu Method, Including Possible Biases, the Complexity of the Calculations and the Generalizability in the Regions Affected by the ASF

While the Lububu method offers significant advantages in ASF diagnosis through the integration of machine learning (ML) and causal inference (CI), it also has notable limitations that need to be addressed for wider applicability.

Possible bias in the Lububu method

Data bias

i. The Lububu method is based on ASF outbreak data, which may be biased in relation to certain regions, farms or diagnostic methods.
ii. If the training dataset lacks different genetic ASF strains, the model may not generalize to new ASF variants.
iii. Selection bias may arise if only severely symptomatic cases are included and mild or asymptomatic ASF infections are neglected.

Bias in the model assumptions

The method assumes causal relationships between disease state (D_t), environmental factors (E_t) and transmission rates (T_t). However, some relationships may be non-linear or influenced by unknown confounding factors, leading to incorrect causal interpretations.

Computational complexity

High computational complexity

i. The integration of causal graphs, Do-Calculus and ML models increases computational complexity.
ii. Neural network-based models often outperform the Lububu method in terms of pure accuracy, as they can capture high-dimensional feature interactions, while causal inference increases interpretability, but at the cost of computational efficiency.

Complexity of feature selection

i. The need to consider observed (X_t) and unobserved (U_t) variables as well as interventions (V_t) make feature engineering complex.
ii. Building causal structures (e.g. DAGs) require expertise and is prone to missing or incorrect assumptions.

Generalizability in ASF-affected regions

Region-specific model performance

i. ASF spreads differently in areas with high livestock density (e.g. China, Europe) than in areas with free-range farming (e.g. Africa, South America).
ii. The training data of the Lububu method may not contain enough variability, leading to over-adaptation to certain conditions.

Limited data availability

i. Many regions affected by ASF lack detailed epidemiological and diagnostic data, making it difficult to train the model on truly representative data sets.
ii. Underreporting of ASF due to poor surveillance systems in certain regions could lead to systematic bias and affect the reliability of the model.

Ethical and practical challenges of interventions

i. The model assumes that interventions (V_t) (e.g. quarantine, vaccination) have an impact on the spread of ASF, but in many regions' vaccination is not yet available or widely implemented.
ii. Biosecurity measures differ significantly between smallholder farms and large commercial farms, so recommendations are context dependent.

Possible Solutions and Future Directions

Defusing prejudices

i. Include different ASF data from multiple regions, including mild, asymptomatic and new ASF strains.
ii. Use transfer learning to adapt the model in different ASF-affected regions.

Computational improvements

i. Develop efficient algorithms to discover causal relationships to reduce computational burden.
ii. Explore hybrid models that balance neural networks for predictive accuracy and causal inference for interpretability.

Improve generalizability

i. Perform regional model validation with real-time data from ASF outbreaks.
ii. Implement adaptive models that adjust to local agricultural conditions and ASF transmission patterns.

Practical Contributions of Lububu Method

The Lububu method offers a novel AI-driven approach to ASF control, veterinary diagnostics and AI ethics, making it highly valuable for epidemic management and disease prediction. Below you will find the key contributions and potential future applications.

Implications for ASF control programs

Early detection and management of outbreaks

i. The Lububu causal AI framework enables early detection of ASF by analyzing symptoms, environmental risks and transmission patterns.
ii. It helps to prioritize interventions such as quarantine measures, movement restrictions and vaccination strategies to reduce the spread of ASF.

Improving surveillance and response strategies

i. ASF outbreak data can be integrated into predictive models to optimize resource allocation in ASF-affected regions.
ii. Governments and veterinary authorities can use AI-driven ASF heatmaps to improve real-time decision making.

Economic and agricultural benefits

i. Reducing ASF outbreaks through AI-based diagnostics can minimize livestock losses and stabilize global pork production.
ii. Smallholder farmers in Africa and Asia can benefit from low-cost, AI-driven ASF surveillance tools.

Effects on veterinary diagnostics

Improvement in diagnostic accuracy and speed

i. Conventional ASF diagnostics (e.g. PCR, ELISA tests) require special equipment and trained personnel.
ii. The Lububu method integrates machine learning (ML) and causal inference (CI) to make fast, interpretable and scalable predictions based on clinical symptoms and risk factors.

Reduction of false positives and false negatives

i. Standard AI models can misclassify ASF symptoms due to correlation-based biases.
ii. The Lububu method improves interpretability by distinguishing causal disease factors from mere correlations, thus reducing diagnostic errors.

Potential for mobile and field applications

i. AI-based ASF diagnostic tools can be implemented in mobile applications, allowing veterinarians to perform assessments in the field without access to a laboratory.

AI ethics in disease diagnosis

Considerations of bias and fairness

i. ASF models trained in region-specific data may not generalize well across different ASF outbreaks.
ii. Ensuring fair model performance across different regions affected by ASF is critical to avoid bias in disease control policy.

Transparency and explainability

i. Many ML models, especially deep learning approaches, are black box systems that make it difficult to interpret AI-driven diagnoses.
ii. The Lububu method emphasizes causal reasoning and ensures that decision making is explainable to veterinarians and policy makers.

Data protection and surveillance risks

i. The integration of AI-based ASF detection into national disease control programs requires careful data protection.
ii. Governments must ensure that farmers' data is stored securely and not used for unethical surveillance practices.

Adaptation of the Lububu method to other disease models

The hybrid ML-CI approach of the Lububu method can be applied to both human and animal health for different diseases:

Human health applications

i. **COVID-19 & influenza:** predicting severity of infection and hospitalization risk based on symptoms and transmission patterns
ii. **Tuberculosis (TB) & Malaria**: Improving diagnosis in resource-limited settings based on clinical and environmental risk factors.
iii. **Chronic diseases (diabetes, cardiovascular):** Identification of causal risk factors for preventive health strategies.

Applications for animal health

i. **Foot and mouth disease (FMD):** AI-supported prediction of livestock diseases for early containment of outbreaks.
ii. **Avian influenza (bird flu):** Improved modeling of disease spread in poultry farms.
iii. **Bovine tuberculosis:** Improving diagnostics in cattle breeding, avoiding economic losses.

Future research directions

Integration with real-time disease surveillance systems

i. Linking AI-based ASF diagnostic models with national veterinary databases to enable real-time outbreak tracking.
ii. Develop mobile ASF surveillance applications that provide instant risk assessments to farmers.

Causal inference for multi-disease modeling

i. Extend the Lububu method to multiple livestock diseases to enable real-time joint disease detection.
ii. Create cross-disease causal diagrams that predict interaction effects between ASF and other swine diseases.

Ethical AI and regulatory compliance

i. Establish guidelines for the ethical use of AI in veterinary medicine and public health.
ii. Working with governments and regulators to ensure transparency and fairness in AI.

Recommendations for Implementing the Lububu Model in Veterinary and Public Health Decision-Making

Integration into disease surveillance systems

i. Deploy the Lububu model in real-time ASF surveillance platforms to enable early outbreak detection and risk assessment.
ii. Link AI-driven diagnostics to national veterinary databases for centralized disease tracking

Improve field diagnostics

i. Develop mobile applications based on Lububu-powered AI for ASF risk assessment by veterinarians in the field.
ii. Training of field staff in the use of AI-based diagnostic tools for rapid decision-making in ASF-prone regions.

Political decision-making and intervention strategies

i. Use Lububu-based insights to inform ASF control policies, including quarantine measures and prioritization of vaccination.
ii. Enable AI-powered decision support for governments and stakeholders to optimize resource allocation during outbreaks.

Ethical and fair use of AI

i. Develop regulatory guidelines to prevent bias in AI-assisted ASF diagnostics.
ii. Promote open-access AI models to support global ASP management.

Conclusion

The Lububu method represents a significant advance in the field of causal machine learning. It offers an approach that combines causality, contextual understanding and adaptability. The Lububu method offers an innovative, interpretable approach to ASF diagnosis, but biases, computational complexity, and regional generalizability remain challenges. Addressing these limitations through data diversity, model optimization and localized validation will improve applicability in practice. The Lububu method bridges the gap between AI and veterinary epidemiology, providing interpretable and scalable ASF diagnostic tools in real time. By integrating causal inference, ML and disease surveillance, this approach has the potential to revolutionize disease management in both human and animal health.

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Conflicts of Interest: The author declare no conflict of interest.

References

Agbo, S. O., Samuel, S. E., & Idoko, D. J. (2022). Expert system-based machine learning analysis for diagnosis and treatment of swine diseases using decision tree, logistic regression and support vector machine algorithms. Retrieved from https://www.ftstjournal.com/uploads/docs/73%20Article%2049%20pp%20364-374.pdf

Aguero, M., Fernández, J., Romero, L., Sánchez Mascaraque, C., Arias, M., & Sánchez-Vizcaíno, J. M. (2003). Highly sensitive PCR assay for routine diagnosis of African swine fever virus in clinical samples. Journal of Clinical Microbiology, 41(9), 4431-4434. https://doi.org/10.1128/JCM.41.9.4431-4434.2003

Bodria, F., Giannotti, F., Guidotti, R., Naretto, F., Pedreschi, D., & Rinzivillo, S. (2023). Benchmarking and survey of explanation methods for black box models. Data Mining and Knowledge Discovery, 37(5), 1719-1778. https://doi.org/10.1007/s10618-023-00894-3

Cai, Z., Yan, H., Li, P., Huang, Z. A., & Gao, C. (2017). Towards secure and flexible EHR sharing in mobile health cloud under static assumptions. Cluster Computing, 20, 2415-2422. https://doi.org/10.1007/s10586-017-0916-7

Chen, N., Zhou, M., Dong, X., Qu, J., Gong, F., Han, Y., ... & Zhang, L. (2020). Epidemiological and clinical characteristics of 99 cases of 2019 novel coronavirus pneumonia in Wuhan, China: A descriptive study. The Lancet, 395(10223), 507-513. https://doi.org/10.1016/S0140-6736(20)30211-7

Cui, P., & Athey, S. (2022). Stable learning establishes some common ground between causal inference and machine learning. Nature Machine Intelligence, 4(2), 110-115. https://doi.org/10.1038/s41563-022-01002-0

Dormann, C. F., Schymanski, S. J., Cabral, J., Chuine, I., Graham, C., Hartig, F., ... & Singer, A. (2012). Correlation and process in species distribution models: Bridging a dichotomy. Journal of Biogeography, 39(12), 2119-2131. https://doi.org/10.1111/j.1365-2699.2012.02701.x

Fernández-Pinero, J., Gallardo, C., Elizalde, M., Robles, A., Gómez, C., Bishop, R., ... & Arias, M. (2013). Molecular diagnosis of African swine fever by a new real-time PCR using universal probe library. Transboundary and Emerging Diseases, 60(1), 48-58. https://doi.org/10.1111/tbed.12012

Liu, Y., Li, Z., Ge, Q., Lin, N., & Xiong, M. (2019). Deep feature selection and causal analysis of Alzheimer's disease. Frontiers in Neuroscience, 13, 1198. https://doi.org/10.3389/fnins.2019.01198

Ljung, L. (2001). Black-box models from input-output measurements. In IMTC 2001. Proceedings of the 18th IEEE instrumentation and measurement technology conference. Rediscovering measurement in the age of informatics (Vol. 1, pp. 138-146). IEEE. https://doi.org/10.1109/IMTC.2001.943680

Lububu, S., & Twum-Darko, M. (2024). Comparative analysis of machine learning algorithms to improve the diagnosis of African swine fever. International Journal of Business Ecosystem & Strategy, 6(5), 121-137. https://doi.org/10.1504/IJBES.2024.10002513

Nunes, J. M. B., Martins, J. T., Zhou, L., Alajamy, M., & Al-Mamari, S. (2010). Contextual sensitivity in grounded theory: The role of pilot studies. The Electronic Journal of Business Research Methods, 8(2), 73-84.

Pearl, J. (2009). Causal inference in statistics: An overview. Statistics Surveys, 3, 96-146. https://doi.org/10.1214/09-SS057

Richens, J. G., Lee, C. M., & Johri, S. (2020). Improving the accuracy of medical diagnosis with causal machine learning. Nature Communications, 11(1), 3923. https://doi.org/10.1038/s41467-020-17780-1

Shimizu, S., Hoyer, P. O., Hyvärinen, A., Kerminen, A., & Jordan, M. (2006). A linear non-Gaussian acyclic model for causal discovery. Journal of Machine Learning Research, 7(10), 2003-2030. http://www.jmlr.org/papers/volume7/shimizu06a/shimizu06a.pdf

Shinde, M. J., & Pawar, S. S. (2015). Comparative study of decision tree algorithm and Naive Bayes classifier for swine flu prediction. International Journal of Research in Engineering and Technology, 4(6), 45-50.

Spirtes, P., Glymour, C., Scheines, R., Kauffman, S., Aimale, V., & Wimberly, F. (2000). Constructing Bayesian network models of gene expression networks from microarray data. Proceedings of the 3rd Annual Conference on Computational Biology, 1-8.

Valiente Kroon, J. A. (2012). Asymptotic simplicity and static data. Annales Henri Poincaré, 13(2), 363-397. https://doi.org/10.1007/s00023-012-0189-3

Van Bavel, J. J., Mende-Siedlecki, P., Brady, W. J., & Reinero, D. A. (2016). Contextual sensitivity in scientific reproducibility. Proceedings of the National Academy of Sciences, 113(23), 6454-6459. https://doi.org/10.1073/pnas.1601049113

Wheeler, G. (2009). Focused correlation and confirmation. The British Journal for the Philosophy of Science. https://doi.org/10.1093/bjps/axp045

Wieder, W. R., Lawrence, D. M., Fisher, R. A., Bonan, G. B., Cheng, S. J., Goodale, C. L., ... & Thomas, R. Q. (2019). Beyond static benchmarking: Using experimental manipulations to evaluate land model assumptions. Global Biogeochemical Cycles, 33(10), 1289-1309. https://doi.org/10.1029/2019GB006287

Zhao, Q., & Hastie, T. (2021). Causal interpretations of black-box models. Journal of Business & Economic Statistics, 39(1), 272-281. https://doi.org/10.1080/07350015.2020.1734410

Zhou, K., Yang, J., Loy, C. C., & Liu, Z. (2022). Learning to prompt for vision-language models. International Journal of Computer Vision, 130(9), 2337-2348. https://doi.org/10.1007/s11263-022-01551-6

Zhu, Y., Zhang, M., Jie, Z., Guo, S., Zhu, Z., & Tao, S. C. (2024). Strategic nucleic acid detection approaches for diagnosing African swine fever (ASF): Navigating disease dynamics. Veterinary Research, 55(1), 131. https://doi.org/10.1186/s13567-024-01173-1

Zsak, L., Borca, M. V., Risatti, G. R., Zsak, A., French, R. A., Lu, Z., ... & Rock, D. L. (2005). Preclinical diagnosis of African swine fever in contact-exposed swine by a real-time PCR assay. Journal of Clinical Microbiology, 43(1), 112-119. https://doi.org/10.1128/JCM.43.1.112-119.2005