

System IoT-AI Based on Microclimate Disease Risk Index for Early Detection of Vanilla Plant Diseases

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Abstract : The vanilla plant (*Vanilla planifolia*) is a high-value commodity, but it is highly susceptible to microclimatic fluctuations and disease attacks, especially stem and root rot closely related to *Fusarium oxysporum f. sp. vanillae*. A review of the literature also shows that temperature, humidity, and shade conditions affect vanilla growth, whereas conventional monitoring approaches often detect disease risk too late. This paper presents a systematic literature study with the help of Google Scholar-based Publish or Perish (PoP), enriched by targeted searches on ScienceDirect and Web of Science, and reported to follow the principles of PRISMA 2020. The synthesis results show that the integration of IoT, microclimate sensors, and AI has the potential to form a more precise Early Warning System through the MDRI index, which is a weighted risk score that collects parameters of temperature, relative humidity, VPD, light intensity, soil moisture, and history of daily conditions. Conceptually, MDRI can be applied to edge devices to provide early warnings, recommendations for cultivation actions, and the basis for data-driven decision-making. This paper emphasizes that the IoT-AI approach is not just a monitoring tool, but the foundation of an adaptive and sustainable vanilla disease risk management system.

Keyword : Vanilla; Early detection; IoT-AI

INTRODUCTION

The vanilla plant (*Vanilla planifolia*), often dubbed "green gold," is the second-highest-valued spice commodity in the world after saffron. The high price of vanilla is driven by the growing demand of the global food, perfume, and pharmaceutical industries for natural vanillin (Adedeji et al., 2020). However, behind its lucrative economic value, vanilla cultivation faces highly complex biological and environmental challenges. These plants are known to be highly sensitive to microenvironmental changes and susceptible to soil-borne pathogens, which are often a major limiting factor in sustainable productivity (Parada-Molina et al., 2022; Sujatha et al., 2010).

One of the deadliest threats to vanilla growers around the world is stem and root rot (BBA) caused by the fungus *Fusarium oxysporum f. sp. vanillae*. These pathogens attack the plant's vascular system, causing rapid wilt that can result in up to 100% total crop failure if not treated early (Koyyappurath et al., 2016; Ramírez-Mosqueda et al., 2015). The agronomic literature consistently shows that population explosions and *Fusarium* infection rates are strongly influenced by microclimatic dynamics. Extreme temperature variations, excessively high relative humidity (RH) above 80%, and irregular light intensity due to poor shade management create an ideal environment for pathogenic spore germination (Parada-Molina et al., 2022; Yuliana et al., 2022).

The main problem in the health management of vanilla plants today is the delay in detection. Farmers generally still rely on visual inspection to identify disease symptoms. However, when visual symptoms such as chlorosis or decay at the base of the stem appear, the infection within the plant tissue usually has reached an advanced stage (Jackulin & Murugavalli, 2022). In this context, the

monitoring paradigm must shift from a reactive approach to a preventive-predictive approach. Digital transformation through the implementation of *the Internet of Things* (IoT) offers a strategic solution by providing the ability to measure the physical parameters of the environment in *real-time* and continuously (Rajak *et al.*, 2023). A network of sensors distributed in vanilla fields can capture micro-second fluctuations in soil temperature, canopy moisture, and *Vapor Pressure Deficit* (VPD) that are not detected by the human senses.

Nonetheless, the accumulation of raw data from IoT sensors alone is not enough to aid decision-making at the farmer level. A layer of artificial intelligence is needed to translate complex environmental data into actionable insights. Machine learning algorithms have the ability to recognize patterns of environmental anomalies that correlate with the early phases of disease incubation (Jackulin & Murugavalli, 2022). Therefore, the development of the Microclimate Disease Risk Index (MDRI) is very crucial. MDRI is designed as a score-based composite index that integrates various microclimate variables to map disease risk levels on a simple numerical scale.

This conceptual paper aims to formulate an MDRI-centric IoT-AI system framework as the foundation of the *Early Warning System* (EWS) in vanilla plants. By integrating a biological understanding of plant-pathogen interactions with cloud computing and intelligent sensors, the system is expected to provide farmers with early warning before pathogens cause permanent damage. These innovations not only aim to reduce economic losses but also support sustainable farming practices by reducing the use of chemical fungicides through more precise and data-driven environmental applications.

Purpose

The main purpose of this conceptual paper is to formulate a *framework* for the integration of IoT and AI technology through the development of *the Microclimate Disease Risk Index* (MDRI) as an instrument for early disease detection in vanilla plants. Specifically, this study aims to:

1. Synthesize the parameters of optimal microclimate requirements for the growth of *Vanilla planifolia*, including critical thresholds of temperature, relative humidity (RH), and *Vapor Pressure Deficit* (VPD) that affect plant susceptibility.
2. Identify environmental risk factors that trigger the development of major pathogens, particularly *Fusarium oxysporum f. sp. vanillae*, based on empirical evidence in the current literature.
3. Analyze the relevance and effectiveness of IoT–AI architectures in processing sensory data into accurate predictive information for precise plant health management.
4. Develop a systematic literature search methodology using *the Publish or Perish* (PoP) tool to ensure transparency, reproducibility, and quality of data synthesized from various globally reputable databases (Google Scholar, ScienceDirect, and Web of Science).
5. Propose a conceptual model of MDRI as an adaptive risk assessment algorithm, which can be implemented by farmers and agricultural technology developers to reduce the rate of yield loss due to diseases.

METHOD

Research Design

This research was designed using a qualitative-descriptive Systematic Literature Study (SLS) approach. The main focus of this method is to identify, evaluate, and interpret all available research findings related to the topics of IoT, AI, and vanilla diseases (Page *et al.*, 2021). This design was chosen to bridge the gap between traditional plant pathology theories and the implementation of smart farming technology.

Search Procedures and Data Sources

The process of collecting literature data is carried out in stages using Publish or Perish (PoP) software. This strategy allows researchers to efficiently sift through thousands of articles based on citation metrics and keyword relevance (Harzing, n.d.).

- Key Data Sources: Google Scholar (for broad coverage), ScienceDirect (for technical and agronomic journal articles), and Web of Science (to ensure inclusion of highly reputable journals/Q1-Q2).

- Search String: > ("vanilla planifolia" OR vanilla) AND (disease OR "stem rot" OR Fusarium OR "early warning" OR IoT OR AI or "machine learning" OR microclimate OR sensor)

PRISMA 2020 Protocol

To maintain transparency and objectivity, the reporting of this study follows the guidelines of *the Preferred Reporting Items for Systematic Reviews and Meta-Analyses* (PRISMA) 2020 (Page et al., 2021). These stages include:

1. Identification: Initial searches using keywords across all databases.
2. Screening: Removal of duplicate articles and filtering of irrelevant titles and abstracts.
3. *Eligibility*: Full-text manuscript review to ensure that articles address the link of microclimate to diseases or IoT/AI technologies.
4. Inclusion: Determination of the final article to be synthesized narratively in the discussion.

Inclusion and Exclusion Criteria

To ensure the quality of the synthesis, the selection criteria are set as follows:

- Inclusion Criteria: (1) Articles published in 2010–2026; (2) Focus on vanilla plants or microclimate-based plant disease models; (3) Discuss IoT sensor technology or AI algorithms; (4) Speak English or Indonesian.
- Exclusion Criteria: (1) Popular articles without *peer review*; (2) Editorials or news reports; (3) Studies that only discuss the economic aspects of vanilla without mentioning environmental factors or diseases.

Data Analysis and Synthesis

The collected data was analyzed using narrative synthesis techniques. Information from various studies was grouped into thematic clusters (microclimate, pathology, and technology) to then draw conceptual conclusions to build the MDRI model. The proposed MDRI formula is based on the weighting of the environmental parameters that most often appear as triggers for infection in the literature reviewed (Newlands, 2018).

RESULTS AND DISCUSSION

1. Dynamics and Stability of Microclimate in Vanilla Cultivation

The stability of the microclimate environment is the main pillar in the success of vanilla (*Vanilla planifolia*) cultivation. As a plant that naturally grows in the shade of tropical forests, vanilla relies heavily on protection from extreme environmental changes. Various studies show that the growth and metabolism of vanilla are directly affected by the interaction between light intensity, air temperature, and humidity (Sujatha et al., 2010). In plantation systems, the use of standing trees or shade nets serves as a biological buffer that keeps the physical parameters of the environment at the optimal range for plants. Without this stability, the physiological character of vanilla can undergo significant changes that hinder its productivity potential.

Too rapid environmental fluctuations or extreme weather conditions often trigger high agronomic risks. For example, an environment that is too open or has low humidity levels will cause plants to experience prolonged periods of water stress (Parada-Molina et al., 2022). This condition not only reduces the comfort of growing plants but also weakens the vanilla's internal defense system. From a physiological point of view, vanilla needs a balance between solar radiation and moisture to avoid cellular stress (Sujatha et al., 2010). Therefore, the stability of the microclimate is not just a cultivation background, but a controlling factor that determines whether plants are able to survive or become susceptible to disease disturbances.

The highly sensitive nature of vanilla to environmental changes makes traditional monitoring methods, such as visual inspection, less effective for early detection of risks. Often, when symptoms of stress or disease are already visible to the naked eye, internal damage to plant tissues has reached an advanced stage (Jackulin & Murugavalli, 2022). These limitations demonstrate the importance of switching to continuous surveillance at the microclimate level with the help of sensor technology (Rajak et al., 2023). By shifting the focus from observing visual symptoms to monitoring environmental data in *real-time*, farmers can identify potential risks before crops show signs of physical decline. This approach provides a stronger foundation for more proactive and data-driven vanilla plantation management.

2. Vanilla's Major Disease Relationship with Environmental Dynamics

Stem and Root Rot (BBA) caused by *the fungus Fusarium oxysporum f. sp. vanillae* is the most significant pathological threat in the global vanilla industry. These infections attack the vascular system of plants, resulting in disruption of nutrient and water transport, often leading to rapid plant death (Ramírez-Mosqueda *et al.*, 2015). The agronomic literature confirms that the severity of this infection is highly dependent on environmental conditions, where excessive moisture in the growing medium and poor drainage act as the main catalyst for the germination of pathogenic spores (Yuliana *et al.*, 2022). Therefore, understanding the patterns of interaction between the presence of pathogens and the physical conditions of the environment is key to an effective plant protection strategy.

From the perspective of plant pathology, the onset of disease is the result of complex interactions in a "disease triangle" involving host, pathogen and environment. Environmental factors, particularly the microclimate around the crown and soil surface, have a dual role in determining the level of infection risk (Newlands, 2018). High air humidity and low air circulation in the planting area create conditions conducive to the development of soil-borne fungi. Studies show that environmental parameters can be used as an early warning indicator, because changes in microclimatic conditions often precede the appearance of visual symptoms of disease in plant tissues (Newlands, 2018).

The application of plant disease risk models is highly dependent on the accuracy of the environmental data used in the forecasting process. The use of data from regional weather stations is often considered inadequate because it is not able to capture very specific microclimate variations in each garden (Mosedale *et al.*, 2024). Temperature and humidity differences between regional data and real conditions under the vanilla heading can lead to errors in risk predictions. This underlies the urgency of developing a *Microclimate Disease Risk Index* (MDRI) based on direct field sensor data, in order to produce an early detection system that is more precise and relevant to actual conditions on the ground (Mosedale *et al.*, 2024).

3. IoT and AI strengthen early detection of plant diseases

The use of *the Internet of Things* (IoT) in the modern agricultural sector serves as a data acquisition layer that works in *real-time* and continuously. Through the use of *smart sensors*, various physical parameters that are crucial for plant growth can be monitored with a high level of precision (Rajak *et al.*, 2023). In the context of vanilla cultivation, IoT infrastructure acts as a "neural system" capable of capturing microclimate fluctuations instantly, including variables such as air temperature, humidity, and leaf wetness. The ability of IoT to provide a stable flow of data without time constraints is the foundation for a much more responsive and accurate monitoring system compared to manual logging methods.

While IoT is tasked with collecting raw data, artificial intelligence and *machine learning* act as inference machines that process the information into predictive insights. Recent literature highlights that AI is not only effective in detecting diseases through image or visual analysis, but also highly reliable in recognizing anomalous patterns in environmental data (Jackulin *et al.*, 2022). Using classification or regression algorithms, the system can identify combinations of microclimatic conditions that are at high risk of triggering pathogenic infections. This integration transforms complex environmental data sets into easy-to-understand risk indicators, making it easier for stakeholders to take targeted preventive actions.

The implementation of this intelligent system offers a strategic advantage in the early detection aspect, especially in the latent phase where the symptoms of the disease are not yet visible to the naked eye. Diseases in vanilla plants are often triggered by an imbalance of environmental conditions that last for a certain period of time before physical symptoms such as decay appear (Jackulin *et al.*, 2022). Sensor-based predictive approaches have the potential to detect threats much faster compared to manual inspections which tend to be reactive. Thus, the application of IoT-AI technology has become a key pillar in the transformation of precision agriculture, enabling proactive risk mitigation to minimize crop losses due to disease attacks.

4. Proposed MDRI Concept

The Microclimate Disease Risk Index (MDRI) is proposed as a synthesis instrument that bridges raw biophysical data with the biological probability of disease emergence in vanilla plants. Conceptually, this index functions as a composite indicator that integrates various microclimate

variables simultaneously to produce a single representative risk value (Newlands, 2018). This approach recognizes that disease risk is not only triggered by a single factor, but is the result of the accumulation of interactions between temperature, humidity, and other physical conditions that take place over a period of time. By summarizing environmental complexity into a simple numerical scale (e.g. 0–100), MDRI allows farmers to objectively monitor land health without having to interpret sensor data individually.

The determination of the MDRI score is based on weighted calculations involving essential parameters such as air temperature, relative humidity (RH), *Vapor Pressure Deficit* (VPD), light intensity, soil moisture, and duration of wet conditions (Mosedale et al., 2024).

In the formula, each s_i parameter is first normalized to the range 0–1 to have a uniform scale before being multiplied by the weight of w_i reflecting the degree of influence of that variable on the life cycle of *the Fusarium* pathogen. This determination of weights is dynamic; can be compiled based on agronomic literature, *expert judgment*, or trained using *machine learning* algorithms that study the correlation between environmental historical data and disease incidence in the field (Newlands, 2018).

The final stage of the implementation of MDRI is the mapping of index values into risk class categories, such as low, medium, high, and very high. This category division functions as a *Decision Support System* that provides guidance for real intervention steps for farmers in the field. For example, when the MDRI value increases because environmental parameters deviate from the vanilla's optimal zone, the system will immediately trigger an early warning before damage to plant tissues occurs. The use of such weighted index approaches is in line with global climate-based crop disease risk modeling trends, making it an adaptive and accurate solution in crop disease mitigation in the era of smart agriculture (Mosedale et al., 2024).

5. IoT–AI system architecture design

The designed system architecture adopts *the concept of Artificial Intelligence of Things* (AIoT), where the integration between sensor hardware and artificial intelligence algorithms works synergistically to produce a responsive early detection system. This structure is divided into four main layers that are interconnected to ensure that the flow of data from the land to the user's hands runs smoothly. The use of this layered architecture is in line with modern trends in precision agriculture that prioritize data processing speed, early warning accuracy, and real-time field data-driven decision-making efficiency (Rajak et al., 2023).

At the basic level, the Sensing Layer acts as a sensory system that acquires microclimatic parameters through various physical sensors strategically placed in the vanilla plantation area. The raw data is then passed to the Edge Layer, which uses ESP32-based microcontrollers to perform pre-processing, such as *noise filtering* and data time synchronization. The advantage of using *edge computing* at this stage is its ability to process data locally before it is sent to the server, thereby reducing *bandwidth load* and speeding up system response time to critical conditions in the field (Rajak et al., 2023).

The next layer is the AI layer, where cleaned environmental data is processed using classification or regression models to automatically calculate MDRI scores. This is where artificial intelligence acts as an inference engine that maps the pattern of microclimate variables to disease risk opportunities (Jackulin & Murugavalli, 2022). The results of this process are then translated to the Application Layer in the form of *visual dashboards, notifications via smartphones, or physical alerts such as LED lights and buzzers* on the ground. With this scheme, farmers not only receive raw data, but also get recommendations for concrete cultivation actions based on the risk status detected.

Coating	Components	Function	Output
Sensing	Sensors temperature, RH, light, soil moisture, <i>leaf wetness</i>	Acquiring microclimate data	Real-time <i>data</i>
Edge	Microcontroller (ESP32) + <i>firmware</i>	Pre-processing, <i>filtering</i> , synchronization	Net data

AI	Classification/regression model	Calculating the risk of disease	MDRI Score
Application	Dashboard, <i>mobile alert</i> , LED/buzzer	Display status and alerts	Action notifications

6. Practical and Strategic Implications of the MDRI System

The implementation of MDRI-based IoT-AI systems in vanilla cultivation has brought a significant transformation from traditional farming patterns to scalable precision agriculture. For farmers, the existence of this risk index functions as a *decision support system* that allows cultivation interventions to be carried out in a timely and targeted manner. For example, instead of watering on a regular schedule, farmers can adjust the water volume based on soil moisture data and recorded VPD values. This not only optimizes the growth of vanilla but also prevents oversaturated conditions of the growing medium, which is a major trigger for the development of *Fusarium* pathogens (Yuliana *et al.*, 2022). In addition, the regulation of light intensity through shade management can be done more accurately before the plant experiences extreme heat stress.

For agricultural extension workers and related institutions, this system provides an objective and *data-driven* monitoring foundation. So far, the monitoring of the health of vanilla plants relies heavily on the capacity of visual observation, which tends to be subjective and often late in detecting symptoms of latent infection. With the MDRI dashboard, extension workers can monitor many land points simultaneously and provide technical recommendations supported by empirical evidence (Rajak *et al.*, 2023). Long-term integration of microclimate data also allows for the formation of a historically valuable database for researchers to understand the behavior of vanilla pathogens in specific regions, such as in dryland or coastal areas.

On a broader scale, the MDRI approach is a crucial adaptation instrument in dealing with climate change uncertainty. Temperature dynamics and erratic rainfall patterns are currently proven to often shift the life cycle of pests and plant disease distribution patterns (Mosedale *et al.*, 2024). With AI capabilities to study environmental trends and dynamically predict risks, the system helps vanilla farmers to remain resilient in the midst of rapid environmental change. Economically, the efficiency of the use of agricultural inputs and the reduction of crop failure due to BBA disease will directly contribute to the stability of farmers' incomes, while maintaining the position of vanilla as a sustainable, superior export commodity.

CONCLUSION

This study concludes that microclimate stability is the main determining factor in maintaining the health of the vanilla plant (*Vanilla planifolia*), considering its highly sensitive nature to temperature and humidity fluctuations in air and soil. This physiological vulnerability is directly correlated with the risk of attack by *the pathogen Fusarium oxysporum f. sp. vanillae*, where an imbalance of environmental conditions is often a major trigger for the occurrence of adverse stem and root rot infections.

Through the synthesis of various reputable literature, the integration of Internet of Things (IoT) technology for *real-time* data acquisition and Artificial Intelligence (AI) as an inference engine proved to be a strategic solution to mitigate these risks in the latent phase. Therefore, the development of the Microclimate Disease Risk Index (MDRI) as a composite index is very feasible to be implemented as the foundation of the Early Warning System. This conceptual innovation enables the transition from reactive visual monitoring to preventive, data-driven cultivation actions, which can ultimately reduce farmers' economic losses and support the sustainability of the vanilla industry in the era of smart agriculture.

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