From Review to Refinement: An Expert-Informed Environmental Diagnostic Model for Stingless Bee Colony Monitoring

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***Abstract*—The resilience of stingless bee colonies has become increasingly challenged by erratic climate conditions and intensified environmental stressors. While previous studies have introduced diagnostic models for monitoring colony health, most remain constrained by a narrow reliance on either environmental or behavioral parameters alone. This study proposes a refined diagnostic model that builds on existing frameworks and is further shaped by expert insights from the field. The model integrates environmental inputs, specifically temperature and humidity, with behavioral activity detected via video analysis to deliver a multi-dimensional assessment of colony status. Through a structured review of the literature and interviews with apiculture experts, we identify critical gaps in conventional systems and translate those findings into a more responsive and field-deployable architecture. The result is an improved model capable of categorizing colony health with greater sensitivity and clarity, designed to support early intervention and long-term monitoring. The model is visualized through comparative schematic diagrams, showing the evolution from a basic environmental-only logic to a more holistic decision-making system.**

***Keywords*—Stingless bees; environmental monitoring; behavioral analysis; diagnostic model; expert-informed refinement**

I. Introduction

Stingless bees are considered one of the most important pollinators in tropical and subtropical regions [1]. They can help in sustaining crop production and balancing ecological systems [2], especially in areas where traditional pollinators like honeybees are in decline. Unlike other bees, stingless bees are more adaptable and are kept in small-scale meliponiculture farms for honey, pollen, and propolis. The existence and health of these colonies impact not only biodiversity but also the economic welfare of rural populations who rely on these products.

Nonetheless, the existence of stingless bee colonies is increasingly threatened by sudden environmental changes, such as erratic temperature changes, long periods of high humidity, and habitat destruction [3]. These stressors often weaken colonies and, in more extreme cases, can lead to colony collapse disorder, in which bees suddenly and inexplicably abandon the hive.

The most common approach to assess the colonies' health remains manual inspection. These methods usually require opening the hive and examining stores of food, brood patterns, and bee activity; however, frequent inspections are invasive and can disturb the colony's microclimate and social thermoregulation, thereby increasing stress on the colony. Moreover, manual checks are typically episodic and depend on the observer's experience and judgment, making them subjective and prone to inconsistency; as a result, important early-warning signals may be missed or detected late. Recent reviews, therefore, highlight the growing role of non-invasive, sensor-based precision-beekeeping and AI methods as complementary tools to reduce disturbance and provide continuous, objective monitoring [4], [5], [6], [7].

To address these problems, technological solutions have been gradually integrated into beekeeping to enable more continuous and less invasive monitoring. However, many existing precision-beekeeping systems primarily rely on a narrow set of environmental parameters, most commonly in-hive and ambient temperature, humidity and sometimes hive weight, measured by simple sensors. While these indicators are valuable for assessing thermostatically performance and colony strength, they do not directly capture behavioral responses such as reduced movement, altered foraging flux, entrance traffic changes, or other anticipatory actions that can precede overt environmental shifts. Consequently, systems that omit behavioral dimensions are limited in their ability to detect early warning signals and critical precursors of colony stress; recent literature therefore recommends integrating video, audio, weight and advanced pattern-recognition methods to improve early diagnostics [8], [9], [10].

Existing stingless bee monitoring systems predominantly focus on either environmental sensing or activity observation in isolation. Environmental-only systems therefore provide useful information about nest microclimate or mass balance, but they are limited in detecting early behavioral responses, such as changes in movement, entrance traffic, or foraging flux, that often precede measurable environmental shifts. Conversely, behavior-only approaches (camera or acoustic monitoring) typically lack concurrent environmental context, which complicates interpretation of causal drivers. In addition, many operational threshold values and alarm rules have been inherited or adapted from Apis-centric studies without systematic validation for Meliponini species, reducing predictive accuracy when applied to stingless-bee colonies in varied ecological settings. Finally, several deployed systems use monolithic, fixed architectures that are difficult to extend to additional sensor modalities or site-specific calibration, constraining adaptability across management regimes and habitats. Recent reviews and empirical studies, therefore, recommend multimodal, modular monitoring architectures and species-specific validation of thresholds to improve early-warning performance for stingless bee management [11], [12], [13], [14].

The motivation for this research arises from the need to bridge these gaps through an integrated, adaptable, and empirically validated diagnostic framework. This study proposes a model that combines temperature and humidity monitoring with automated behavioral analysis using computer vision, refined through expert consultation to ensure parameter thresholds align with local field realities. By embedding the system within a modular architecture, it supports future expansion to include additional environmental or behavioral indicators as required by practitioners.

This study aims to address the following research questions:

1) How can environmental monitoring and bee activity analysis be integrated into a unified diagnostic framework for stingless bee colony health?

2) What key environmental and behavioral parameters are critical to accurately classify colony health status?

3) How can expert validation be incorporated to refine the model and enhance its practical applicability in real-world beekeeping?

The remainder of this study is organized as follows: Section II reviews relevant literature on stingless bee monitoring systems and related technologies. Section III presents the proposed initial model, outlining its structure and components. Section IV describes the expert review process and the subsequent model refinements. Section V reports the results and analysis of expert feedback. Section VI discusses the findings, identifies limitations, and suggests directions for future research. Section VII concludes the study.

II. Literature Review

The deterioration in stingless bee health is frequently signaled by declining population levels, decreased foraging activity, and irregular behavioral patterns. These symptoms often result from the complex interplay between environmental disturbances and biological stress [1]. Fluctuating temperature and humidity, increasing pollutant exposure, and unpredictable climate variability have been identified as key contributors to destabilizing colony health. As an example, sudden temperature fluctuations can disrupt bees' navigation systems, causing lower foraging efficiency and disorientation on the way back to the hive [15]. Pesticides and heavy metals introduced to the food chain further weaken immune systems, diminishing the vitality of colonies [3].

Due to this ecological fragility, stingless bees are viewed as effective indicator of broader environmental changes. Among all environmental variables, temperature is by far the most important. It controls the metabolic rate, enzyme activity, and developmental processes within colonies. Departures from ideal temperature ranges either above or below will disturb normal physiological functions, impair social cohesion, and increase susceptibility to infections [16]. Excessive heat can cause high water loss, energy loss, and loss of internal hive control, while the cold slows metabolism and essential cleaning tasks vital to hygiene. At the same time, relative humidity affects the microclimate important for rearing brood and for the integrity of wax. These reasons explain why the parameters are considered essential indicators for assessing the impact of human activity on the environment and monitoring the health of the colony.

Monitoring of stingless bees has improved with the incorporation of technology. Real-time environmental monitoring, such as the Internet of Things (IoT), can utilize temperature, humidity, gas, and even sound sensors to check on health systems [17]. Though these sensor technologies facilitate continuous monitoring, early detection of risks, and automated data collection, their practical application is still hampered by significant obstacles like integration difficulties, drifting sensors, and unreliable power supplies.

Modeling environmental risks has received great focus because of its ability to predict. Many models combine several environmental factors like temperature, humidity, and air conditioning to create risk assessment models that can provide dynamic alerts and automation in decision-making [18]. Advanced computation methods, like statistical methods and machine learning, have developed these models. Even with the availability of data, there is still a challenge in creating usable models that are interpretable for the field in different ecological contexts. In response, recent systems have integrated web-based dashboards for real-time sensor data visualization using Flask and similar frameworks [19]. While these platforms improve usability, their performance depends on reliable connectivity, efficient data processing, and interface responsiveness, areas still under active development [20].

Growing interest in bee rehabilitation has driven parallel innovation in system architectures. Several projects have applied LoRa communication protocols to enable wide-area data collection in low-power field settings [21]. Predictive frameworks based on real-time sensor data have also been proposed to mitigate health risks [22]. Beyond colony-level monitoring, studies on plant resource availability underscore the broader ecological factors affecting bee behavior and resilience [23]. A system-based approach for understanding colony decline recommends modeling across behavioral, environmental, and management layers [24], aligning well with recent IoT-enabled diagnostic platforms [25].

Stingless bee research increasingly emphasizes smart hive solutions. Low-cost microcontrollers combined with DHT22 temperature sensors and weight modules have formed the basis for continuous environmental assessment [26]. Additionally, machine learning applications have been used to analyze health signals and optimize colony management based on predictive patterns [27]. Environmental data streams, including microclimate, hive weight, and diurnal cycles, are now routinely collected to inform health assessments and enhance productivity [28].

Swarm detection and motion analysis have also evolved through radar-based systems capable of capturing flight frequency and trajectory with high precision [29]. Computer vision applications, particularly those using YOLO-based object detection, offer automated monitoring of colony entrances, detecting forager numbers, pollen load, and potential threats such as varroa mites [30]. In Brazil, stingless bee monitoring has been strongly aligned with ecological preservation and economic sustainability, driving the integration of IoT infrastructure with policy support [2]. Simultaneously, lightweight and modular systems, often relying on open-source hardware such as Arduino and ESP8266, continue to play a central role in decentralized deployments [31].

Further efforts have RFID-based data collection for evaluating pesticide exposure, which remains one of the most pressing threats to pollinator viability [32]. Policy recommendations increasingly emphasize the need for regulatory frameworks that ensure sustainable beekeeping practices while supporting the adoption of digital technologies [33]. In this context, wireless systems for tracking hive parameters, such as temperature and honey yield, are proving vital to optimizing production strategies [17],[22]. RFID also supports individual bee tracking, facilitating more nuanced behavioral research [34].

Integrated systems such as HiveLink [35] and IntelliBeeHive [36] illustrate how visual data, sensor readings, and AI analytics can converge to offer non-invasive, real-time diagnostic support. These systems demonstrate how timely insights can reduce colony loss and improve beekeeper response. Complementing this direction, Liang [37] proposed a hybrid vision-audio health evaluation model that achieved over 92% classification accuracy, showing particular promise in low-light or acoustically active environments.

Recent developments emphasize not only precision but also environmental breadth. Real-time monitoring solutions now include air quality indices such as CO_2, NH_3, and NOx concentrations measured through LoRa networks [38]. The iBees system, for instance, integrates GPS, thermal, and humidity tracking with cloud-based storage for production optimization [39]. Rosli et al. [40] further expanded this design with the addition of weighing and pressure sensors for hive condition profiling. These solutions highlight the continuous evolution of intelligent beekeeping, reflecting growing demands for accuracy, usability, and adaptability in diagnostic system design.

Finally, diagnostic expert systems like MoViCES, paired with mobile diagnostic tools such as Dr. Kelulut, reflect a broader shift toward accessible, user-centric tools built on the Model-View-Controller paradigm [41]. These platforms enable real-time hive inspection using embedded borescopes and interface logic designed to support non-expert users. Together, these technological pathways form the basis for next-generation diagnostic systems aimed at securing stingless bee populations through adaptive, evidence-driven monitoring.

III. Proposed Initial Model

Compared to existing stingless bee monitoring approaches, which typically focus on either environmental sensing or activity observation in isolation, this study proposes an integrated diagnostic model that combines environmental parameters (temperature and humidity) with behavioral indicators (bee entry/exit frequency). This dual-source data approach enables earlier and more reliable detection of colony stress. Additionally, the classification thresholds are not arbitrarily set; they are refined through expert consultation, ensuring that the system aligns with practical field conditions. The architecture is designed with modularity and scalability in mind, allowing the integration of additional sensors in future iterations. This combination of environmental–behavioral integration, expert-validated thresholds, and expandable architecture addresses key limitations in existing systems and enhances applicability for real-world meliponiculture.

The environmental parameters, such as temperature and humidity, are widely acknowledged as primary indicators of hive conditions. In early-stage research and prototype planning, these two variables were selected as the core inputs for the proposed diagnostic framework. The rationale behind this choice was twofold: first, temperature and humidity sensors are readily available at low cost, and second, these environmental metrics directly influence key biological processes within the stingless bee colony, including brood development, foraging efficiency, and thermoregulation.

In addition to monitoring environmental parameters, the proposed system integrates a behavioral-monitoring module to quantify colony activity. A video camera is placed at the hive entrance to capture continuous footage of bee traffic. Recorded video is processed with a YOLO-based object detection algorithm to identify and count individual bees per frame. These counts are aggregated over time to generate an activity index that reflects foraging and hive-traffic dynamics. Significant deviations from the colony's baseline activity, such as sudden drops in bee traffic during normally busy foraging periods, can signal environmental stressors, disease onset, or other disruptions. By integrating this behavioral stream with environmental temperature and humidity data, the system achieves enhanced sensitivity in detecting early-warning signs that may not manifest in environmental parameters alone [42],[43],[44],[45].

The conceptual model, as shown in Fig. 1, hereafter referred to as the Proposal Model, was designed to accept temperature and humidity readings, compare them against defined thresholds, and generate a basic health classification for the colony. The output is presented in one of three health categories: Healthy, Medium-Healthy, and Least-Healthy, each represented by a range of percentage scores (71 to 100%, 30 to 70%, and 0 to 29%, respectively). This scoring range is intended to give beekeepers an intuitive understanding of their colony's status, without requiring specialized knowledge to interpret raw sensor data.

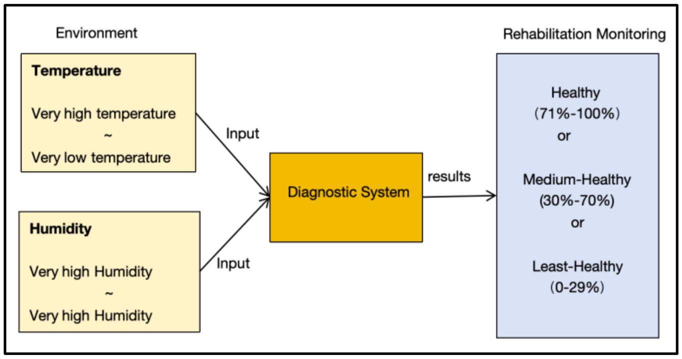

Fig. 1. The conceptual model.

The system begins with environmental sensing units placed within or adjacent to the hive. Two major environmental factors are processed:

Temperature: measurements beyond 25℃ to 34℃ are not optimal. Temperatures over 35℃ may lead to overheating of the brood and a reduction in the activity of worker bees. On the other hand, slowing metabolism and foraging are risks at temperatures below 20℃ [46].

Humidity: fostering fungal growth may occur with excessive humidity over 75%, whereas below 50% contributes to desiccation of the brood and pollen stores [47].

The three health categories: Healthy (71 to 100%), Medium-Healthy (30 to 70%), and Least-Healthy (0 to 29%), were calibrated based on optimal temperature and humidity ranges for stingless bee colonies reported in previous studies. Published data indicate that brood development and colony stability are best maintained within 25 to 34 °C and 60 to 85% relative humidity. These threshold values were further refined through consultation with six domain experts, incorporating observational data from two local meliponiculture sites. The combination of literature-based ranges and expert validation ensures that the classification rules reflect both empirical evidence and local field conditions, thereby improving diagnostic reliability and reducing false alerts.

Once inputs are captured, the model uses a rule-based approach to capture deviation from the optimal range. Each input is assessed individually. In the case that both parameters reside within the defined safe zone, the model outputs a Healthy classification. If one variable deviates while the other is acceptable, the system designates the colony as Medium-Healthy. If both exceed warning thresholds, the system marks the colony as Least-Healthy, indicating it is at risk and requires closer examination.

This system makes it possible to track and analyze health status over time. Data from multiple time points can be collected to map out and analyze defined changes over time. For example, persistent classification as Medium-Healthy signals potential unaddressed stress that, if unaddressed, could result in sudden collapse.

Even though the Proposal Model is easy to use and understand, it has some limitations. It considers the relationship between the environment and the colony as fixed and therefore oversimplifies complex systems. It does not account for minor shifts in temperature or even the tiny changes in the environment that bees respond to, such as clustering or fanning. Moreover, environmental parameters do not sufficiently depict the internal processes of the colony, especially in the case of behavioral cues signaling distress long before temperature or humidity changes can be detected.

Moreover, external environmental conditions could alter humidity and temperature readings temporarily, which might activate distress signals. This reinforces the need for a system that goes beyond environmental inputs and considers the cross-validation of the signals with behavioral indicators, such as activity and resting rhythms, foraging habits, and motion density around hive entrances.

Understanding these limitations, the next section incorporates expert feedback to explain how precisely their input was used to improve the model. These insights induced a number of changes that resulted in the creation of the more thorough behavior-inclusive, diagnostic model framework.

IV. Expert Review and Model Refinement

A. Purpose of Expert Review

Prior to field deployment, it is essential for diagnostic models to undergo validation not only through technical testing but also via theoretical scrutiny by domain experts. The purpose of conducting an expert review at this development stage is to evaluate the conceptual soundness, structural feasibility, and practical applicability of the proposed environmental diagnostic model. Expert feedback helps uncover blind spots, refine assumptions, and ensure that system design aligns with the operational context of stingless bee rehabilitation.

B. Expert Panel and Review Scope

A panel of six domain experts was assembled, selected based on their academic and applied experience in the fields of meliponiculture, environmental monitoring, and system modeling. Each expert was invited to participate in a structured review process using a detailed questionnaire.

The scope of the review encompassed four functional aspects of the model: the conceptual framework linking environmental variables to colony health, the diagnostic module responsible for classification based on sensor data, the behavioral monitoring module enhanced by object detection, and the system architecture including modularity, scalability, and usability.

C. Review of Instrument Design

The expert review was conducted using a structured questionnaire designed to support both quantitative assessment and qualitative feedback. The instrument was organized into four sections, aligned with the functional modules of the model. Each section included closed-ended items on a three-point Likert scale: "Agree, no modification", "Agree, with modification", and "Disagree", as well as open-text fields to capture elaborative suggestions.

The questionnaire design was informed by validation practices in information systems and agricultural technology research. Particular attention was paid to clarity, neutral phrasing, and accessibility across disciplinary backgrounds.

1) Conceptual framework: Evaluates the theoretical basis of the model, particularly its capacity to represent the relationship between environmental stressors (temperature and humidity) and colony health. Items assess whether the model adequately reflects the real-world dynamics of stingless bee rehabilitation.

2) Diagnostic module: Assesses the model environmental sensing component, including the use of DHT22 sensors, the design of health classification thresholds, and the practicality of data capture methods in field conditions.

3) Behavioral monitoring module: Focuses on the integration of computer vision, particularly YOLO-based activity detection, and its relevance for monitoring early indicators of colony stress.

4) System architecture: Evaluates the structure of the system from the perspective of modularity, upgradeability, and end-user usability, including questions related to interface logic, data separation, and adaptability to new sensors.

The instrument emphasized ethical standards, ensuring expert anonymity, voluntary participation, and informed consent.

D. Evaluation Criteria

The evaluation criteria were structured to assess the scientific rigor, operational viability, and ecological relevance of the model. These included:

1) Accuracy of environmental variable selection: Whether temperature and humidity sufficiently capture key influences on stingless bee colony health.

2) Diagnostic reliability: Ability of the classification module to process sensor data, apply thresholds, and produce actionable health scores.

3) Behavioral analysis validity: Effectiveness of the activity detection scheme and its adaptability to field conditions.

4) System modularity and scalability: Capacity for future extension, and separation of functional layers (data capture, processing, interface).

Experts were invited to provide improvement suggestions, highlight oversights, and recommend additional system capabilities where applicable.

E. Questionnaire Administration and Data Collection

Questionnaires were distributed electronically to the six selected experts. Each received a complete packet including a system overview, visual schematics of the model, and an explanation of the review purpose.

The structured responses were compiled and analyzed thematically. Results indicated strong agreement on the model conceptual clarity, with minor modifications suggested for threshold ranges and behavior classification granularity.

Insights gained from this review directly informed the revision of the improved model, ensuring that the final prototype is both scientifically grounded and practically deployable in real-world meliponiculture contexts.

V. Results and Analysis of Expert Feedback

Gaining feedback through the expert review process revealed both the strengths and weaknesses of the environmental diagnostic model. The systematic evaluation and open-ended commentary provided by six experts in the domain allowed for the appraisal of the model integrity, feasibility, and technical scope. Their responses were crucial to the refinement process of the model which took place prior to prototyping and implementation.

In summary, specialized consensus recognized that temperature and humidity are the crucial parameters for the well-being of stingless bee colonies. Focus group members argued that there exists sufficient literature and empirical evidence—both for and field data—to support these factors as significant for brood survival and foraging activity. While some specialists proposed to study additional factors like pesticide, rainfall, or wind, most respondents believed that these inclusions would be too complex for the model, adding unnecessary system complexity and making data collection impractical. Therefore, the model was considered to have an adequately narrow scope for its initial phase while still allowing for these additional factors to be included in later revisions.

Reviewers concentrated on the empirical thresholds as the classification logic and stressed the necessity to define these values more rigorously. These critiques were addressed in the revised model which incorporated predefined empirical ranges for temperature and humidity based on field study data and data collected at the sites. This change was made to improve the objectivity and transparency of the classification procedure, especially in the differentiation of Healthy, Medium Healthy, and Least Healthy. Besides the fixed boundaries, the precise measurement and observation nexus was simplified to integrate more behavioral input to strengthen classification consistency.

The incorporation of computer vision to monitor activity patterns was positively received. Experts agreed that bee behavior often reflects underlying stress before environmental parameters shift dramatically. The use of YOLO-based movement tracking was considered a practical and innovative approach, provided lighting conditions and camera angles are well-controlled. Some experts encouraged exploring audio analysis in future model iterations, especially for applications in low-light environments or enclosed hives where visual data may be unreliable.

Further feedback addressed the overall system architecture, particularly the modularity and potential for scalability. Experts viewed the separation of data collection, processing, and interface layers as beneficial for future upgrades. The improved model maintains compatibility with additional sensors and analytics modules, allowing the system to evolve with user needs and technological advancements.

The revised diagnostic model, presented as Fig. 2, reflects the collective input received through the expert review process. The visual representation now illustrates the integration of clearly defined environmental thresholds, behavior scoring modules, and a composite health assessment logic. While some expert recommendations—such as multi-factor environmental correlation—were deemed outside the current scope due to limited data availability, the model retains flexibility for phased development.

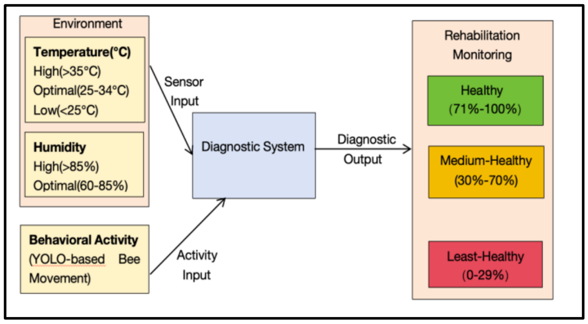

Fig. 2. The improved diagnostic model.

A total of six domain experts participated in the validation of the proposed environmental diagnostic model. The evaluation combined structured questionnaire items with open-ended feedback to capture both quantitative agreement levels and qualitative improvement suggestions.

Regarding environmental parameter selection, five experts (83%) fully agreed that temperature and humidity are the most critical indicators for stingless bee colony health, supported by literature and field experience. One expert (17%) recommended the inclusion of additional variables such as pesticide exposure, rainfall, and wind speed for future model iterations.

For threshold definitions, the original model expressed temperature and humidity using broad qualitative categories (ranging from "very high" to "very low"). Based on expert feedback and literature review, these were replaced with quantitative ranges. The temperature threshold was refined to 25℃ to 34℃, aligning with documented optimal conditions for brood development and adult bee activity, and narrowing the previous qualitative extremes to improve measurement precision. The humidity threshold was set to 60% to 85%, representing a narrowing from the broader original qualitative range. This adjustment reduces classification ambiguity and better reflects the optimal moisture conditions for maintaining brood health, as confirmed by preliminary site measurements.

In terms of behavioral monitoring, all six experts (100%) endorsed the integration of computer vision for activity tracking. Four (67%) supported the use of entry/exit frequency and foraging intensity as primary indicators, while two (33%) proposed adding in-nest movement metrics for more granular behavioral assessment. Future work will investigate the feasibility of incorporating these additional in-nest movement metrics, as they could provide deeper insights into colony therm.

On system architecture, five experts (83%) agreed that the modular design separating data collection, processing, and user interface layers supports scalability and future integration of additional sensors or analytics modules. One expert (17%) highlighted the need for detailed user interface customization to match local beekeeper practices. To address this, future work will include developing a customizable user interface framework that allows adaptation to different cultural, linguistic, and operational contexts, thereby enhancing the model's usability and facilitating its broader adoption.

Overall, the statistical results indicate strong expert consensus on the core environmental and behavioral parameters, with constructive recommendations aimed at refining threshold precision and expanding the behavioral dataset. The incorporation of these validated ranges and prioritized behavioral metrics into the improved model enhances both its scientific robustness and its practical applicability in real-world beekeeping contexts.

By aligning expert opinion with empirical research and real-world constraints, the refinement process has strengthened both the diagnostic logic and the system relevance to field practitioners. The structured feedback not only confirmed the conceptual robustness of the model but also identified practical adjustments that improve usability, interpretability, and future integration potential. These insights will guide the next stage of model validation and system deployment.

VI. Discussion

The integration of environmental parameters with bee activity data provides a holistic perspective on colony health, addressing limitations in traditional monitoring approaches that rely solely on manual observation or single data types. Expert feedback further supports the model's practical feasibility, highlighting its potential to inform proactive interventions. However, the current threshold definitions remain in a preliminary stage, as they were derived from a combination of literature-based ranges and short-term data from a limited number of colonies under specific seasonal and geographic conditions. This restricted dataset may not capture variability due to climate, floral availability, or hive management practices in other regions.

To achieve more definitive calibration, future work should follow a structured roadway: 1) conduct longitudinal monitoring across multiple colonies, seasons, and habitat types; 2) integrate external environmental datasets (local meteorological data) for contextual correlation; 3) perform statistical sensitivity analyses to determine optimal threshold boundaries; and 4) validate the refined model through cross-site field trials with independent beekeeper cohorts. This multi-stage approach will enable the thresholds to be both scientifically robust and broadly applicable to diverse meliponiculture contexts.

Compared to existing stingless bee monitoring systems that rely solely on either environmental sensors or behavioral observations, the proposed model delivers a more comprehensive health assessment by integrating both data sources into a unified diagnostic framework. The inclusion of expert-validated thresholds ensures that the classification logic is both scientifically grounded and field-ready. Furthermore, the modular architecture allows for future upgrades, such as adding sound analysis, air quality sensing, or advanced behavioral metrics, without requiring major system redesign. This combination of data integration, expert refinement, and practical scalability enhances the model's originality and applicability for sustainable stingless bee colony management [46], [48].

VII. CONCLUSION

This study has presented the development and refinement of an environmental diagnostic model tailored to the health monitoring needs of stingless bee colonies. Recognizing the limitations of conventional inspection methods and single-parameter sensing systems, the model integrates both environmental variables namely temperature and humidity and behavioral indicators derived from computer vision analysis to generate a composite health assessment. This multidimensional framework enables earlier detection of colony stress and delivers actionable insights in a format suitable for field practitioners.

To ensure conceptual clarity and practical relevance, the model underwent a structured expert review involving six specialists across meliponiculture, environmental sensing, and system design. Their feedback validated the scientific basis of the model, affirmed the choice of key parameters, and highlighted important refinements, such as clearer threshold definitions and improved interpretability. As a result, the revised model incorporates empirically grounded environmental ranges, activity-based behavioral detection, and a modular architecture that supports future system enhancement.

Future work will focus on deploying the system in live apiary environments to evaluate real-time performance, robustness under variable weather conditions, and end-user interaction feedback. In parallel, work will continue on refining the behavioral analysis component, exploring the use of hybrid vision and sound recognition to enhance accuracy in low-visibility settings.

In conclusion, this expert-informed environmental diagnostic model represents a promising step towards more intelligent, interpretable, and scalable monitoring tools for stingless bee colony rehabilitation. By combining ecological understanding with low-cost sensing and expert knowledge, it contributes not only to applied beekeeping technologies, but also to the broader goal of sustaining pollinator health in increasingly stressed environments.

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