e-ISSN 2828-0490
JURNAL MEDIA COMPUTER SCIENCE

An Integrated IoT–AI Architecture for Precision Beekeeping: Sensing, Data Communication, Colony-State Intelligence, and Decision-Oriented Actions

Pipit Utami [1]; Mashoedah [2]; Hanif Nurkhalis [3]; Muhammad Akhdan Nafi' [4]; Wulan Savitri [5]; Widya Prastowo [6]; Diah Wulan Safitri [7]; Fajar Dwi Saputra [8]

[1,2,3,4,5,6,7,8] *Electronics Engineering Education, Faculty of Engineering, Universitas Negeri Yogyakarta*

Email: [1]pipitutami@uny.ac.id

How to Cite :

Utami, P., Mashoedah, Nurkhalis, H., Nafi', M.A., Savitri, W., Prastowo, W., Safitri, W.D., Saputra, F.D. (2024). An Integrated IoT–AI Architecture for Precision Beekeeping: Sensing, Data Communication, Colony-State Intelligence, and Decision-Oriented Actions. Jurnal Media Computer Science, 3(2)

ARTICLE HISTORY

Received [26 Juni 2024]
Revised [28 Juli 2024]
Accepted [31 Juli 2024]

KEYWORDS

Precision Beekeeping, Internet Of Things, Smart Beehive,Multimodal Sensing, Architecture-Oriented Synthesis, Decision-Oriented Systems.

ABSTRAK

Perlebahan presisi memanfaatkan teknologi Internet of Things (IoT) dan kecerdasan buatan (AI) untuk pengelolaan koloni lebah madu berbasis data, namun sebagian besar sistem yang dikembangkan masih berorientasi pada pemantauan. Penelitian ini bertujuan mensintesis arsitektur sistem precision beekeeping berbasis IoT–AI dan mengidentifikasi kesenjangan integrasi yang membatasi dukungan pengambilan keputusan. Kajian dilakukan melalui systematic literature review terhadap 50 artikel terindeks Scopus periode 2015–2024 menggunakan pendekatan PRISMA dan architecture-oriented synthesis yang menganalisis keterpaduan lapisan sensing, komunikasi, kecerdasan, dan keputusan. Hasil menunjukkan dominasi sensing dan akuisisi data, sementara keterkaitan antara keluaran analitik dan keputusan operasional masih terbatas sehingga banyak sistem belum menutup alur dari inferensi ke aksi. Temuan ini menegaskan bahwa keterbatasan utama bersifat arsitektural, bukan teknologis. Studi ini memposisikan reference architecture sebagai kerangka analitis untuk sistem smart beehive end-to-end yang berorientasi keputusan, dengan implikasi bagi pengembangan perlebahan presisi yang lebih terintegrasi dan aplikatif pada skala kecil dan menengah.

ABSTRACT

Precision beekeeping increasingly adopts Internet of Things (IoT) and artificial intelligence (AI) technologies, yet most existing systems remain monitoring-centric. This study synthesizes the architectural characteristics of IoT–AI precision beekeeping systems and identifies integration gaps that constrain decision-oriented operation. A systematic literature review of 50 Scopus-indexed studies published between 2015 and 2024 was conducted using a PRISMA-based selection process and an architecture-oriented synthesis across sensing, communication, intelligence, and decision layers. The results reveal a strong emphasis on sensing and data acquisition, while analytical outputs are weakly linked to operational decision-making, preventing most systems from closing the loop from inference to action. These findings suggest that the main limitation is architectural rather than technological. Accordingly, this study positions a reference architecture as an analytical framework for end-to-end smart beehive systems, with implications for more integrated and practical applications in small- and medium-scale beekeeping operations.

INTRODUCTION

Honeybee colonies constitute a foundational component of agricultural ecosystems through their role in pollination, which directly sustains crop productivity, biodiversity, and food security. Recent studies consistently emphasize that pollination services provided by honeybees remain irreplaceable for many food crops, positioning beekeeping not only as an ecological necessity but also as an economic activity with tangible implications for rural livelihoods and local value chains (Huho et al., 2024). In parallel, improvements in beekeeping practices and technology adoption have been associated with increased honey yields and enhanced income stability, particularly for small- and medium-scale producers (Tulu et al., 2020).

Building on this ecological and economic relevance, beekeeping practices have gradually shifted from episodic manual inspection toward data-driven management. Precision beekeeping refers to a data-driven approach to beehive management that integrates sensing technologies and analytics to continuously monitor honeybee colonies and support timely management decisions. Precision beekeeping has emerged as a response to persistent challenges such as colony collapse, climate variability, delayed intervention, and labor-intensive hive inspection routines. This paradigm leverages Internet of Things technologies to enable continuous, non-intrusive monitoring of hive conditions and colony activity, thereby reducing the need for frequent physical inspections while improving situational awareness at the colony level (Meikle et al., 2023; Zacepins et al., 2017). Early IoT-based beehive systems predominantly relied on a limited set of variables, particularly temperature, humidity, and hive weight, demonstrating that these measurements can function as reliable proxies for thermoregulation, brood stability, foraging dynamics, and seasonal productivity patterns (Edwards-Murphy et al., 2015; Gil-Lebrero et al., 2017).

As monitoring requirements became more complex, subsequent research extended this foundation by incorporating additional sensing modalities such as acoustics, vibration, gas sensing, and vision-based monitoring. These modalities provide richer representations of collective colony behavior and internal stress responses, enabling the detection of events such as swarming preparation, abnormal activity patterns, or metabolic imbalance within the hive (Ho et al., 2022; Potamitis et al., 2023). In parallel, artificial intelligence techniques including machine learning, deep learning, and computer vision have been increasingly applied to infer colony states, identify anomalies, and support predictive assessments of colony health and productivity (Anwar et al., 2022; Zheng et al., 2024). While these developments signal growing technological maturity, they also expose structural limitations related to how sensing, analytics, and action are integrated at the system level.

These limitations are most clearly observed in the fragmented nature of many smart beehive implementations. Existing systems frequently treat sensing, data communication, analytics, and application layers as loosely coupled or independent components, often relying on isolated wireless sensor networks for data acquisition without coherent orchestration across layers. Such fragmentation introduces inefficiencies and inconsistencies that constrain the translation of collected data into timely and context-aware operational responses (Cecchi et al., 2020; Ntawuzumunsi et al., 2023). Moreover, the absence of explicit end-to-end architectural thinking means that advanced analytics outputs frequently remain disconnected from practical decision-making processes at the apiary level, limiting their real-world impact (Doinea et al., 2024; Guruprasad & Leiding, 2024).

This architectural disconnect is further reflected in the weak linkage between data analytics and operational action. Although sophisticated algorithms are increasingly employed to process multi-modal sensor data, resulting insights are commonly delivered through descriptive dashboards or basic alerts that provide limited guidance for intervention. As a consequence, beekeepers may struggle to translate analytical results into effective management actions that enhance colony health and productivity (Doinea et al., 2024; Progoulakis et al., 2021). These challenges are compounded by the limitations of traditional manual hive inspections, which are widely criticized for being time-consuming, disruptive to colony dynamics, and unsuitable for continuous monitoring, thereby reinforcing the need for integrated and automated monitoring approaches (Ho et al., 2022; Săcăleanu et al., 2024).

Against this background, the present study formulates an integrated IoT–AI architecture for precision beekeeping that explicitly connects sensing, data communication, colony-state intelligence, and decision-oriented actions within a coherent system framework. Rather than emphasizing individual sensors, algorithms, or platforms, the proposed approach foregrounds architectural integration as a prerequisite for transforming raw data into actionable knowledge that supports timely and informed decision-making by beekeepers.

The contribution of this study is threefold. First, it offers an architecture-level synthesis of Scopus-indexed precision beekeeping studies, revealing structural patterns and integration gaps that are not readily visible in component-centric analyses. Second, it introduces a functional sensor taxonomy that frames sensing technologies as proxies for biological and operational colony states, enabling more consistent interpretation across heterogeneous systems. Third, it advances a decision-oriented intelligence perspective, positioning analytical outputs as integral elements of operational support rather than as isolated monitoring results.

To address this gap, the study adopts an architecture-oriented literature synthesis that systematically examines how sensing, communication, intelligence, and decision mechanisms are integrated across existing IoT–AI precision beekeeping systems. These contributions are conceptually summarized in Figure 1, which situates the present study within the broader research landscape and illustrates the shift from component-based solutions toward integrated, decision-relevant IoT–AI architectures for precision beekeeping.

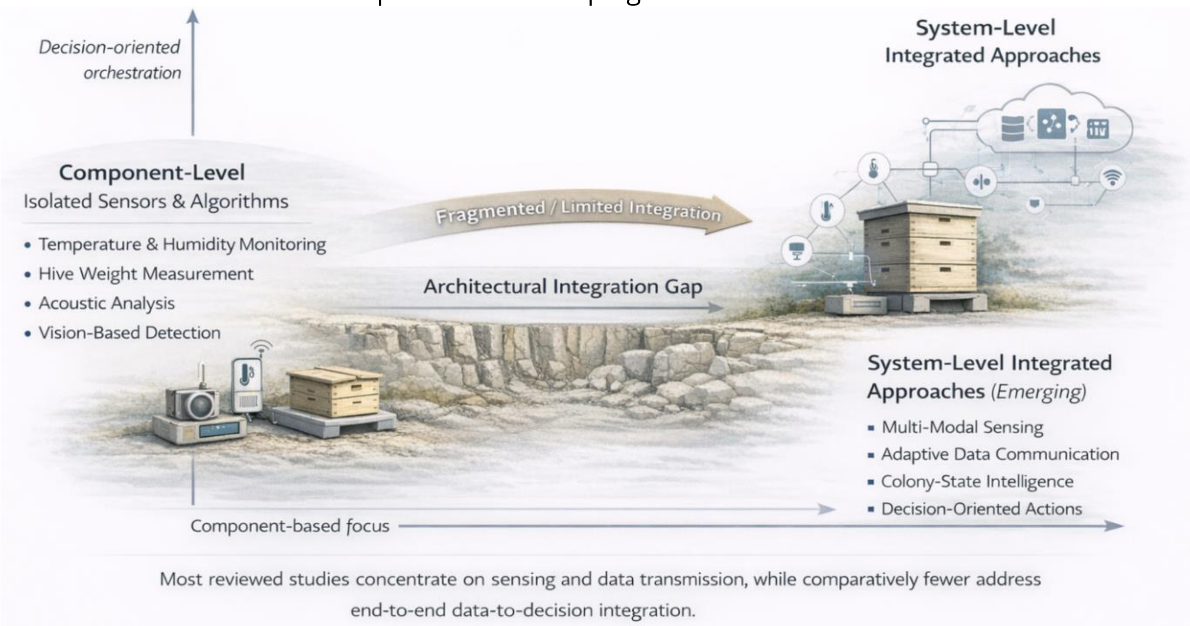

Figure 1. Research positioning and contribution landscape of precision beekeeping systems

Conceptual map illustrating the evolution of precision beekeeping research from component-centric approaches toward integrated, system-level architectures, emphasizing the alignment of sensing, communication, analytics, and decision-support within an end-to-end IoT–AI framework.

Theoretical Background

Precision Beekeeping as a Socio-Technical System

Scopus-indexed studies increasingly conceptualize the beehive as a cyber–physical–biological system in which physical structures, biological organisms, and digital technologies operate as an integrated whole. Within this framework, the beehive constitutes the physical layer, honeybees form the biological layer, and Internet of Things infrastructures together with data analytics platforms represent the cyber layer. Continuous digitization of hive monitoring enables real-time acquisition of environmental and biological signals, bridging physical and biological processes with digital representations that can be analyzed remotely (Kviesis et al., 2023). This perspective emphasizes that colony health and productivity emerge from cross-layer interactions rather than isolated components.

This systemic framing aligns with the theory of honeybee colonies as superorganisms, where collective behavior and adaptive responses cannot be reduced to individual bees. Empirical evidence shows that foraging efficiency, brood regulation, and resilience to stress arise from coordinated colony-level dynamics, particularly under external pressures such as environmental variability, pathogens, or resource scarcity (Faurot-Daniels et al., 2020; Gajger et al., 2020). Consequently, effective monitoring must prioritize collective states rather than individual activity.

Colony-level states such as stress, stability, and productivity are therefore inferred indirectly using proxy indicators derived from continuous sensing data. Variations in hive temperature, humidity, and weight have been shown to correlate with disruptions in brood development, foraging behavior, and overall colony performance (Meikle et al., 2023; Robles-Guerrero et al., 2024). Sudden thermal deviations or unexpected weight losses, for example, frequently signal stress events or productivity decline, providing actionable cues for management intervention (Underwood et al., 2023).

Multi-modal sensing strengthens these inferences by integrating heterogeneous data streams. Combining temperature, humidity, acoustic, and vibration measurements enables more robust representations of emergent colony behavior and improves sensitivity to subtle stressors that remain undetected in single-sensor systems (McKinnon et al., 2023; Nilsson et al., 2024; Robles-Guerrero et al., 2024).

Sensing Technologies for Colony Monitoring

Temperature, humidity, and hive weight sensors are consistently reported as primary modalities for monitoring colony conditions. Temperature sensing is justified by its direct role in brood thermoregulation, which must be maintained within narrow limits for larval development (Guo et al., 2021). Hive weight measurements reflect nectar flow, honey accumulation, and population dynamics, serving as practical indicators of foraging success and productivity, although careful calibration and contextual interpretation remain necessary (Novák et al., 2021). Humidity sensors characterize hive microclimate conditions that influence brood health and metabolic processes, even though reported biological correlations vary across studies (Calderita et al., 2020).

Additional insights are obtained through acoustic, vibration, gas, and vision-based sensing. Acoustic sensors capture collective sound patterns linked to activity levels and swarming preparation (Magdin et al., 2020), while vibration sensors detect structural signals associated with bee movement or external disturbances, albeit with limited large-scale validation (Javed et al., 2020). Gas sensors, particularly those measuring carbon dioxide or volatile compounds, are explored as indicators of respiration and ventilation adequacy, requiring cautious integration with complementary data (Magdin et al., 2020). Vision-based systems provide contextual information on forager traffic and entrance behavior, supporting assessments of colony vitality while introducing challenges related to lighting, occlusion, and data volume (Girotti et al., 2020).

Across these modalities, sensor outputs are consistently interpreted as functional proxies rather than direct biological measurements. Temperature, humidity, or weight data acquire meaning only when contextualized alongside behavioral and environmental information, enabling more reliable inference of colony-level states (Guo et al., 2021).

e-ISSN 2828-0490
JURNAL MEDIA COMPUTER SCIENCE

Table 1. Sensor Types and Functional Roles in Smart Beehive Monitoring

Synthesized from Scopus-indexed studies on precision beekeeping and smart beehive monitoring.

Sensor Type	Measured Parameter	Colony Function Represented	Typical Use Case
Temperature sensor	Internal and ambient hive temperature	Thermoregulation and brood stability	Detecting abnormal thermal conditions associated with brood stress, winter survival risk, or overheating
Humidity sensor	Relative humidity inside the hive	Brood development and moisture balance	Monitoring conditions influencing larval health, fungal growth risk, and ventilation efficiency
Weight sensor (load cell)	Hive weight variation over time	Foraging activity and honey production dynamics	Estimating nectar flow, honey accumulation, and sudden weight loss related to swarming or colony collapse
Acoustic sensor (microphone)	Sound frequency and amplitude patterns	Colony activity and behavioral state	Identifying swarming preparation, queen-related anomalies, and stress-induced collective behavior
Vibration sensor	Structural and comb vibration signals	Collective movement and disturbance response	Detecting external disturbances, predator intrusion, or abnormal internal activity
Gas sensor (CO_2, VOCs)	Gas concentration within the hive	Colony respiration and air quality	Assessing ventilation adequacy and early indicators of overcrowding or metabolic stress
Vision-based camera	Visual activity patterns at hive entrance	Forager traffic and colony vitality	Counting incoming and outgoing bees and identifying abnormal entrance behavior
Bee counter (optical or infrared)	Ingress–egress counts	Foraging efficiency and population dynamics	Quantifying daily activity rhythms and detecting sudden population decline
Environmental sensor	External conditions (light, rainfall, wind)	Environmental context affecting foraging	Relating colony activity to weather variability and seasonal patterns
GPS or location sensor	Geographic position of the hive	Apiary security and spatial monitoring	Theft detection, hive relocation tracking, and spatial management in large-scale apiaries

Table 1 synthesizes sensor types commonly reported in Scopus-indexed precision beekeeping studies and maps them to the colony functions they represent. Sensors are framed as proxies for biological and operational states such as thermoregulation, foraging dynamics, collective behavior, and environmental interaction. The synthesis does not imply simultaneous deployment within a single system, but reflects dominant functional roles observed across heterogeneous implementations.

Data Communication Technologies in Apiary Contexts

Data communication forms an essential enabling layer that connects in-hive sensors with processing and visualization platforms. Commonly adopted technologies include Wi-Fi, LoRaWAN, Zigbee, and cellular networks, selected according to deployment constraints. Wi-Fi supports high data rates for image or audio transmission, whereas LoRaWAN enables long-range, low-power monitoring in remote apiaries. Zigbee offers a balance between range and energy efficiency for localized sensor networks (Bartos et al., 2024; Hadjur et al., 2022).

The literature highlights trade-offs among range, power consumption, scalability, and data rate. LoRaWAN provides extended coverage with low energy usage but limited bandwidth, while Wi-Fi delivers high throughput at the cost of increased power consumption, reducing suitability for long-term battery-powered deployments (Bartos et al., 2024; Terence et al., 2024). Despite their importance, reliability, latency, and fault tolerance remain unevenly evaluated, with few studies systematically examining system resilience under connectivity disruptions (Abdollahi et al., 2022; Hadjur et al., 2022).

AI and Colony-State Intelligence

Artificial intelligence techniques are increasingly applied to infer colony states from multi-modal sensor data. Machine learning methods, including decision trees, support vector machines, and neural networks, are widely used for classification, prediction, and anomaly detection based on acoustic, thermal, and environmental inputs. Convolutional neural networks further support vision-based analysis for behavior recognition and anomaly detection from image or video streams (Robles-Guerrero et al., 2023). Pattern recognition approaches have been shown to effectively transform multi-modal non-verbal sensory signals into objective, high-level inferences using convolutional neural networks, reducing reliance on subjective manual assessment and supporting automated state interpretation (Utami et al., 2022). Colony states are operationalized through metrics reflecting stress, stability, and productivity, derived from correlations among temperature, humidity, weight, and acoustic patterns. By integrating sensor-derived indicators with observed behavioral trends, analytical frameworks approximate the dynamic condition of the colony as a whole (Robles-Guerrero et al., 2023).

Nonetheless, limitations persist regarding data availability, model generalization, and real-time deployment. Variability in sensor data quality affects model robustness, while generalization across apiaries and environmental contexts remains challenging. Computational constraints and integration with existing workflows further limit real-time implementation, underscoring the need for architectural designs that balance analytical sophistication with practical feasibility (Robles-Guerrero et al., 2023). These conceptual perspectives provide the analytical lens through which existing IoT–AI precision beekeeping studies are systematically examined and synthesized in the subsequent methodological section.

Research Methodology

This study adopts an architecture-oriented systematic synthesis to examine how IoT–AI technologies are designed, integrated, and operationalized in precision beekeeping research. The methodological approach is positioned between a fully systematic and a semi-systematic review, combining structured protocols to ensure transparency and rigor with sufficient flexibility to capture architectural patterns across heterogeneous studies. Such an approach is commonly employed in IoT-based agriculture and beekeeping research, where system designs, reporting styles, and evaluation metrics vary substantially across publications (Astuti et al., 2024; Danieli et al., 2023).

Study Design and Search Strategy

Systematic review methodologies in IoT-based agriculture typically rely on predefined protocols to minimize bias, including explicit search strategies, inclusion and exclusion criteria, and structured data extraction procedures (Danieli et al., 2023). In contrast, semi-systematic approaches allow iterative refinement of search terms and analytical focus, enabling broader coverage of emerging technologies while retaining methodological discipline (Astuti et al., 2024). Given the architectural focus of this study, a hybrid strategy is adopted to balance completeness with analytical depth. The review emphasizes system-level organization rather than isolated performance metrics, enabling identification of integration patterns and structural gaps that are not readily observable through performance-based synthesis alone.

Study Identification, Inclusion, and Exclusion Criteria

The study identification and screening process followed a structured yet pragmatic workflow to ensure transparency while maintaining an explicit system-level focus. Literature was retrieved exclusively from the Scopus database using a predefined Boolean search strategy, as summarized in Figure 2. The initial query, limited to publications between 2015 and 2024, yielded 71 records. Successive filtering by document type, language, and source category reduced the corpus to journal articles and conference papers written in English, resulting in 56 eligible studies. Review articles, books, and non-empirical publications were excluded at this stage to ensure that the synthesis was grounded in concrete system implementations rather than conceptual discourse.

Subsequent screening applied a concise set of inclusion and exclusion principles oriented toward architectural relevance. Included studies explicitly addressed IoT technologies within a honeybee or beekeeping context and reported at least one operational system component, such as sensing, data communication, analytics, system action, or platform design. Studies were excluded when they focused solely on biological analysis without IoT implementation, addressed algorithms or signal processing in isolation from system architecture, presented conceptual reviews without implementation detail, or examined IoT applications outside the beekeeping domain. Application of these criteria resulted in a final corpus of 50 studies, forming a coherent and technically grounded basis for the architecture-oriented synthesis reported in Table 2.

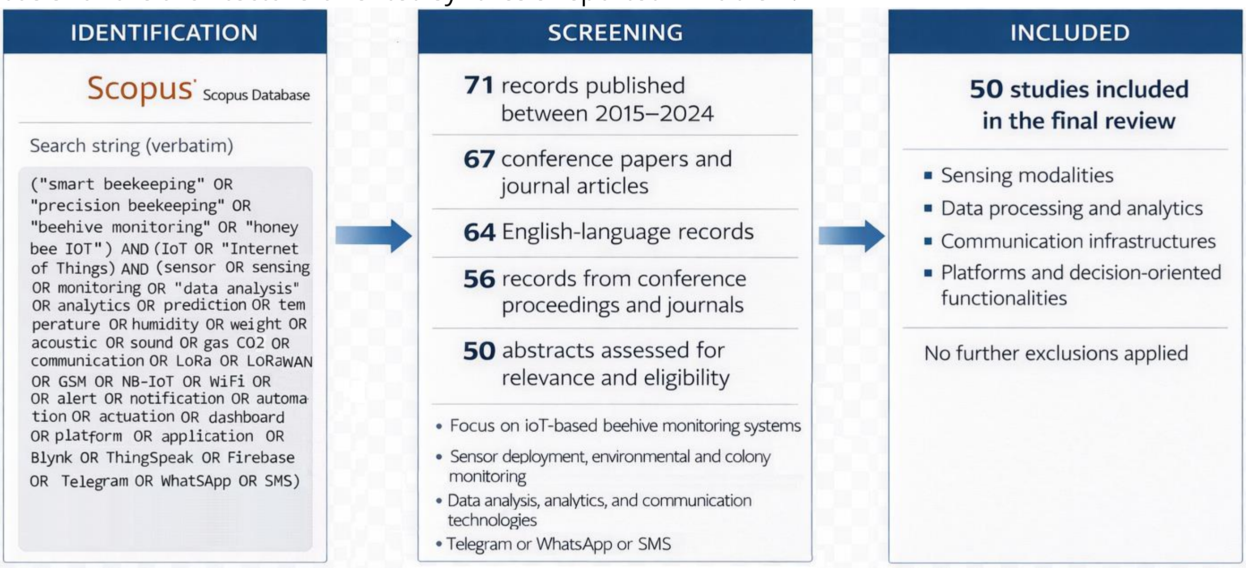

Figure 2. PRISMA-based study selection flow diagram

Figure 2 depicts the PRISMA-based workflow used to construct the review corpus. The diagram outlines the sequential stages of record identification, screening, eligibility assessment, and final inclusion of Scopus-indexed studies, ensuring transparent reporting of inclusion and exclusion decisions.

Quality Assessment and Data Extraction

Methodological quality and technical relevance are assessed using criteria adapted from established systematic review frameworks, including PRISMA-guided evaluation practices (Navarro et al., 2020; Terence et al., 2024). Each included study is examined with respect to system design clarity, sensing modalities, communication technologies, analytical methods, and reported operational outcomes. This structured assessment supports consistent evaluation across heterogeneous implementations and mitigates bias introduced by varying reporting standards. Data extraction focuses on architectural components rather than performance outcomes alone. Key elements include sensing configurations, communication protocols, intelligence methods, user interfaces, and decision-support mechanisms. By emphasizing architectural roles and interactions, the extraction process enables synthesis of design patterns and integration depth across studies.

Architecture-Oriented Classification Framework

To enable cross-study synthesis, an architecture-oriented classification framework is employed to organize reviewed studies according to functional layers, including sensing, data communication, data processing and intelligence, and application-level decision support. Similar stratified frameworks are widely used in IoT research to clarify how heterogeneous components interact within complex systems (Nsoh et al., 2024). This layered abstraction facilitates comparison of studies that differ in implementation details but share common architectural functions. The results of this classification are summarized in Table 2, which aligns reviewed studies with architectural layers and highlights their relative presence across the corpus. The table serves as an analytical lens to reveal structural imbalances and integration gaps within current IoT–AI precision beekeeping research.

Table 2. Architecture-Oriented Synthesis of IoT–AI Precision Beekeeping Studies (n = 50)

Architectural Layer (x/50)	Dominant Technical Focus	Integrated Synthesis Insight
Physical Sensing and Actuation (31/50)	Environmental and colony-condition sensing, including temperature, humidity, hive weight, acoustics, vibration, and visual data capture	Research at this layer prioritizes reliable data acquisition, indicating a strong monitoring orientation with limited coupling to higher-level system functions
Data Acquisition and Communication (22/50)	Data transmission and networking infrastructures such as WiFi, LoRa, LoRaWAN, GSM, NB-IoT, BLE, and MQTT	Communication mechanisms are widely adopted but often function as standalone enablers rather than integrated components of decision-driven architectures
Data Processing and Intelligence (29/50)	Rule-based analytics, machine learning, deep learning, and computer vision for colony-state interpretation and prediction	Analytical capabilities are increasingly sophisticated, yet outputs are frequently descriptive or predictive without direct operational linkage
Application and Decision Support (16/50)	Visualization dashboards, early warning systems, operational recommendations, and decision-support interfaces for beekeepers	Decision-oriented applications remain underrepresented, revealing a persistent gap between analytical insights and actionable system-level decisions

Table 2 presents an architecture-oriented synthesis of the reviewed Scopus-indexed studies by mapping dominant technical contributions to functional architectural layers. The values (x/50) indicate the number of studies addressing each layer, reflecting relative research emphasis rather than performance metrics. This synthesis highlights patterns of concentration and underrepresentation across sensing, communication, intelligence, and decision-support layers.

Cross-Study Comparability and Analytical Consistency

Cross-study comparability is achieved through standardized terminology and consistent categorization of architectural elements, enabling coherent analysis across diverse hardware platforms, software stacks, and deployment contexts. Rather than normalizing performance metrics, the study harmonizes descriptions of system roles and integration depth, which supports meaningful comparison of architectural designs (Matei & Cocoşatu, 2024; Terence et al., 2024). Where appropriate, qualitative aggregation is used to identify recurring patterns and divergences across studies. Overall, this methodology provides a structured yet flexible foundation for analyzing IoT–AI precision beekeeping systems at the architectural level. By combining PRISMA-guided rigor with architecture-oriented classification, the approach supports systematic identification of design tendencies, integration gaps, and opportunities for advancing decision-oriented smart beehive systems.

RESULTS AND DISCUSSION

The following discussion synthesizes architectural insights derived from the reviewed Scopus-indexed literature. Drawing on the methodological approach described in Section 3, it examines how architectural layers within IoT–AI–based precision beekeeping systems are designed, interconnected, and operationalized to generate actionable value. Rather than emphasizing isolated component performance, the analysis highlights recurring system-level patterns, degrees of integration across layers, and the extent to which architectural choices support meaningful decision-making in beekeeping management.

Results

Architecture-Oriented Synthesis of Precision Beekeeping Systems

The architecture-oriented synthesis reveals a clear imbalance in research emphasis across system layers. Physical sensing and data acquisition dominate the literature, reflecting a strong orientation toward monitoring and data collection ((Ho et al., 2022; Zacepins et al., 2017). Communication infrastructures such as LoRa, GSM, and NB-IoT are widely adopted as enabling technologies, yet are rarely examined in terms of latency, scalability, or implications for decision timeliness (Anwar et al., 2022). Although data processing and intelligence layers increasingly employ machine learning and computer vision techniques, analytical outputs remain largely descriptive or predictive, with limited formal linkage to operational decision-making (Zheng et al., 2024).

Table 3 extends the synthesis by mapping the design space of IoT–AI architectures observed across the reviewed studies. The table highlights how combinations of sensing modalities, communication protocols, and intelligence mechanisms form recurring architectural configurations rather than fully integrated end-to-end systems. These configurations reflect dominant research trajectories while also exposing gaps in decision-support integration.

Table 3. Design Space of IoT–AI Architectures for Precision Beekeeping Synthesized from Scopus-Indexed Studies

Architectural Layer	Representative Components	Relative Presence in Literature	Analytical Notes
Sensing (Foundational Layer)	Temperature, humidity, hive weight	Dominant	Consistently reported across studies as primary environmental and colony-state indicators
	Acoustic sensing, vibration sensing	Common	Frequently used for activity monitoring and anomaly detection

Architectural Layer	Representative Components	Relative Presence in Literature	Analytical Notes
	CO_2 / gas sensing	Limited	Appears in a small subset of studies focusing on internal hive conditions
	Optical bee counters, imaging-based sensing	Limited–Emerging	Used mainly for bee counting and visual inspection tasks
Communication Network (Enabling Layer)	LoRa, LoRaWAN	Common	Favored for long-range, low-power monitoring scenarios
	GSM, NB-IoT	Common	Used where cellular infrastructure is available
	Wi-Fi, BLE	Limited	Typically applied in local or experimental setups
	MQTT	Supporting	Mentioned as a messaging protocol rather than a primary research focus
Intelligence (Interpretation Layer)	Rule-based analytics	Dominant	Widely adopted for threshold-based alerts and basic decision support
	Machine learning	Growing	Applied to classification and condition assessment tasks
	Computer vision (bee counting, activity recognition)	Growing	Limited by data availability and deployment complexity
	Edge intelligence	Emerging	Explored for latency reduction and local preprocessing
	Cloud-based forecasting and anomaly detection	Emerging	Typically implemented offline or in batch processing
Decision-Oriented Outcomes	Dashboards and visualization	Common	Almost universally reported as the primary interface for beekeepers
	Alerts and notifications	Common	Mostly rule-based and informational
	Operational recommendations	Limited	Rarely formalized but reported in some studies
	Supervised actions	Rare	Human-in-the-loop actions such as ventilation or heating control
	Autonomous actions	Very rare	Experimental and not representative of mainstream practice

Table 3 summarizes dominant architectural configurations identified across the reviewed studies by combining sensing, communication, intelligence, and application components. The table characterizes the breadth of design choices explored in the literature and illustrates how most systems emphasize monitoring-oriented architectures over decision-oriented integration.

e-ISSN 2828-0490
JURNAL MEDIA COMPUTER SCIENCE

Across the reviewed studies, architectural layers are commonly organized according to a bottom-up abstraction principle, where physical sensing constitutes the foundational layer enabling subsequent communication, intelligent processing, and application-level functionalities. This ordering reflects the dominant structure observed in Scopus-indexed precision beekeeping systems rather than an explicit operational workflow. Table 4 synthesizes architectural layers, their functional roles, and associated integration gaps. The analysis indicates that while sensing and communication layers are relatively mature, the intelligence and decision layers often lack tight coupling with operational actions. As a result, system outputs are frequently limited to visualization or alerting functions without closing the loop toward actionable interventions.

Table 4. Architectural layers, roles, and integration gaps in precision beekeeping systems

Architectural Layer	Primary Role	Typical Technologies	Common Output	Observed Gap
Sensing (Foundational Layer)	Acquisition of environmental and colony-state data	Temperature and humidity sensors, hive weight sensors, acoustic and vibration sensors, optical sensors, gas sensors	Raw and preprocessed sensor data	Heterogeneous sensor deployment without standardized integration across modalities
Communication Network (Enabling Layer)	Transmission of data from hives to processing units	LoRa, LoRaWAN, GSM, NB-IoT, Wi-Fi, BLE, MQTT	Time-series data streams	Limited discussion of communication reliability, latency, and scalability impacts on analytics
Intelligence (Interpretation Layer)	Transformation of data into descriptive or predictive information	Rule-based analytics, machine learning, computer vision, edge and cloud analytics	Activity indicators, anomaly detection results, predictive insights	Analytics often decoupled from operational decisions and rarely integrated across layers
Decision-Oriented Outcomes	Support of beekeeper decision-making	Dashboards, alerts, visualization platforms, recommendation modules	Informational alerts and visual summaries	Predominantly monitoring-oriented outputs with limited decision support and rare actuation

Table 4 aligns architectural layers with their functional roles and highlights recurring integration gaps reported across the literature. The synthesis underscores disparities between data acquisition capabilities and the translation of analytical outputs into decision-oriented system actions.

Multi-Modal Sensing and Communication Configurations

Robust colony observation is increasingly supported through the integration of multiple sensing modalities, including temperature, humidity, acoustic signals, and hive weight. Combining heterogeneous sensors enhances reliability by allowing cross-validation of inferred colony states and mitigating uncertainty associated with single-sensor measurements (Hadjur et al., 2022; Wachowicz et al., 2022). Spatial placement strategies further influence data quality and system effectiveness. Environmental sensors are typically positioned within the hive to capture microclimate conditions, while weight sensors are placed beneath the hive to monitor resource dynamics. Acoustic sensors are often located near hive entrances to capture foraging activity without disrupting internal colony processes (Wachowicz et al., 2022).

Communication configurations supporting these sensing setups commonly rely on long-range, low-power technologies such as LoRaWAN, complemented by Wi-Fi or cellular networks where higher data throughput is required. Table 5 summarizes dominant sensing and communication configurations reported across the reviewed systems.

Table 5. Multi-modal sensing and communication configurations in precision beekeeping systems

Sensor Modality	Spatial Placement	Data Characteristic	Communication Strategy	Design Trade-off
Temperature and humidity sensors	Inside hive core or brood area	Low-frequency, continuous time-series data	LoRa, LoRaWAN, GSM, NB-IoT	Low power consumption and long-term monitoring versus limited temporal granularity
Hive weight sensors	Beneath hive stand or base platform	Low-frequency numerical data reflecting colony load changes	LoRa, GSM, NB-IoT	High relevance for production monitoring but sensitive to mechanical noise and calibration drift
Acoustic sensors	Inside hive or near entrance	High-frequency audio signals requiring preprocessing	Wi-Fi, local storage, occasional GSM upload	Rich behavioral information versus high data volume and energy demand
Vibration sensors	Attached to hive body or frame	Event-driven or high-sampling-rate signals	Local processing with selective transmission via GSM or Wi-Fi	Effective for activity detection but prone to environmental interference
Optical bee counters	Hive entrance	Discrete event counts or short image sequences	Local processing with Wi-Fi or GSM	Accurate traffic estimation versus sensitivity to lighting and occlusion
Imaging devices (cameras)	Hive entrance or external observation points	High-dimensional visual data	Wi-Fi or local storage with batch upload	Enables visual inspection and computer vision analytics but incurs high bandwidth and power costs
CO_2 / gas sensors	Inside hive chamber	Low-frequency concentration measurements	LoRa, GSM	Potential indicator of colony metabolism versus limited validation and sensor drift

Table 5 maps combinations of sensing modalities and communication technologies employed in precision beekeeping systems. The synthesis illustrates how multi-modal sensing is frequently paired with energy-efficient communication protocols to balance data richness, power consumption, and deployment feasibility.

Colony-State Intelligence and Decision-Oriented Actions

Inferred colony states are translated into alerts, recommendations, or suggested actions through a combination of automated analytics and predefined thresholds. Elevated temperatures, abnormal acoustic patterns, or rapid weight changes commonly trigger alerts that notify beekeepers of potential stressors such as overheating, disease presence, or resource depletion (Danieli et al., 2023). Decision-support interfaces predominantly take the form of web-based dashboards and mobile applications that aggregate sensor data and present trends, alerts, and recommendations in an interpretable format (Catania & Vallone, 2020; Danieli et al., 2023). While these interfaces improve situational awareness, most systems rely on supervised decision-making, where human judgment remains central. Table 6 synthesizes how inferred colony states are mapped to decision-oriented actions. The table highlights the predominance of advisory systems over autonomous interventions, reflecting both technical limitations and risk considerations associated with automated hive management (Doinea et al., 2024; Falcão et al., 2024).

Table 6. Mapping colony-state intelligence to decision-oriented actions

Detected State	Data Source	Intelligence Method	Recommended Action
Abnormal temperature or humidity	Temperature and humidity sensors	Rule-based threshold analysis	Alert notification to beekeeper for environmental adjustment
Sudden hive weight loss or gain	Hive weight sensors	Time-series trend analysis, rule-based detection	Notification indicating possible swarming, harvesting period, or abnormal colony activity
Increased acoustic activity	Acoustic sensors	Signal processing, feature extraction, classification	Alert suggesting inspection for swarming or colony disturbance
Irregular vibration patterns	Vibration sensors	Event-based analysis, pattern recognition	Warning indicating possible external disturbance or internal colony stress
High CO_2 concentration	CO_2 / gas sensors	Threshold-based monitoring	Alert recommending hive ventilation check or inspection
Abnormal bee traffic at hive entrance	Optical bee counters	Computer vision-based counting and classification	Notification suggesting abnormal foraging behavior or colony imbalance
Visual signs of colony stress or anomalies	Imaging devices (cameras)	Computer vision and image analysis	Recommendation for manual inspection of hive condition
Potential disease or parasite indicators	Acoustic, optical, or image data	Machine learning or pattern-based anomaly detection	Advisory alert suggesting closer inspection or intervention

Table 6 summarizes how analytical outputs derived from colony-state inference are translated into alerts, recommendations, or automated actions. The synthesis reveals a strong emphasis on supervised decision support, with limited implementation of fully autonomous control mechanisms.

Integration Enablers and Persistent Structural Gaps

Higher levels of system integration are enabled by advances in sensor miniaturization, low-power communication protocols, and the increasing availability of edge and cloud computing resources. Edge–cloud collaboration supports real-time analytics while reducing bandwidth and energy constraints by processing data closer to the source (Junior et al., 2021). Despite these advances, structural gaps persist across the reviewed architectures. Limited interoperability among devices, insufficient user-centered interface design, and weak coupling between intelligence outputs and automated actions constrain the realization of fully integrated decision-support systems (Danieli et al., 2023; Hadjur et al., 2022). Table 7 synthesizes key enablers of system-level integration and their commonly reported limitations across the reviewed Scopus-indexed studies.

Table 7. Enablers of system-level integration in precision beekeeping architectures

Integration Enabler	Architectural Layer(s) Affected	Functional Contribution	Limitation Observed in Reviewed Studies
Multi-sensor integration	Sensing, Intelligence	Improves robustness of colony-state interpretation through combined signals	Integration often limited to simple aggregation without true cross-modal fusion
Edge–cloud task partitioning	Sensing, Communication, Intelligence	Reduces latency and communication load via local preprocessing	Edge intelligence remains constrained by hardware capability and energy
Long-range, low-power communication	Communication	Enables continuous monitoring in remote apiaries	Reliability, latency, and scalability impacts are rarely evaluated in depth
Standardized data ingestion and messaging	Communication, Intelligence	Facilitates data transfer and system interoperability	Data formats and interoperability are seldom standardized across systems
Cloud-based analytics and visualization	Intelligence, Decision-Oriented Outcomes	Supports historical analysis and monitoring dashboards	Outputs remain largely informational with limited decision logic
Rule-based alerting mechanisms	Intelligence, Decision-Oriented Outcomes	Translates detected anomalies into actionable notifications	Alerts are rarely formalized into decision policies or adaptive strategies
Energy-aware system design	Sensing, Communication	Supports long-term deployment under field conditions	Energy performance is inconsistently reported and weakly validated

Table 7 synthesizes technological and organizational enablers that support deeper architectural integration, including sensor capabilities, communication standards, and computational resources. The table also highlights recurring barriers that limit end-to-end integration and scalability.

Value Creation from Sensing to UMKM-Level Benefits

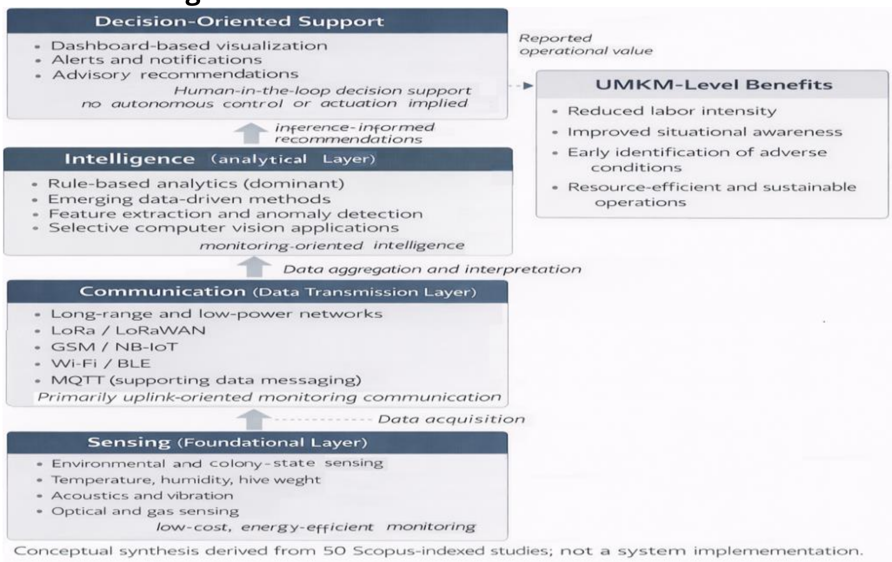

Figure 3. Value creation pathway from sensing to UMKM-level benefits.

e-ISSN 2828-0490
JURNAL MEDIA COMPUTER SCIENCE

Beyond technical considerations, integrated IoT–AI architectures create tangible value for small- and medium-scale beekeeping operations. Continuous monitoring reduces labor intensity by minimizing manual inspections while enabling timely interventions based on real-time data (Cecchi et al., 2020; Hadjur et al., 2022). Figure 3 illustrates the value creation pathway from sensing to UMKM-level benefits, linking technical integration with ecological and economic outcomes. UMKM-level beekeeping operations, defined in this study as micro, small, and medium-scale enterprises operating under resource constraints (small-scale and resource-constrained beekeeping operations). By supporting healthier colonies, reducing hive losses, and improving productivity, precision beekeeping systems contribute to both economic resilience and ecological sustainability (Guruprasad & Leiding, 2024; Kontogiannis, 2024). Figure 3 conceptualizes how integrated sensing, communication, intelligence, and decision-support layers generate operational, economic, and ecological value for small- and medium-scale beekeeping enterprises. The pathway emphasizes the translation of technical capabilities into actionable benefits at the UMKM level.

Discussion

Integrated Discussion

The integrated discussion consolidates evidence derived from the architecture-oriented synthesis of IoT–AI precision beekeeping studies. Across the reviewed literature, a consistent pattern emerges in which integration depth across sensing, communication, intelligence, and decision layers is interpreted as a research gap rather than a technological limitation. Several studies explicitly argue that the absence of comprehensive integration reflects an underdeveloped conceptual and architectural framework, not insufficient sensing accuracy or analytical capability (Hadjur et al., 2022). This interpretation aligns with findings showing that existing technologies are already capable of supporting deeper end-to-end integration, yet their potential remains underutilized in practice.

Within the analyzed systems, architectural designs remain predominantly monitoring-centric. While multi-modal sensing, edge–cloud analytics, and machine learning techniques are increasingly adopted, decision-support mechanisms are largely limited to dashboards and alert-based notifications. Such mechanisms primarily provide descriptive or predictive information without structured recommendation logic or adaptive decision pathways that systematically translate intelligence outputs into operational actions (Guruprasad & Leiding, 2024). As a result, the loop between inference and action is often left open, reinforcing the fragmentation observed across system layers.

A further limitation identified across the reviewed studies relates to methodological and reporting heterogeneity. Many systems rely on secondary data and employ diverse sensing configurations, data formats, and evaluation metrics, which restricts comparability and hinders the synthesis of transferable architectural knowledge (Mezher et al., 2021). In addition, the lack of contextual detail concerning local environmental and operational conditions reduces confidence in generalizing findings across different beekeeping settings, potentially leading to misinterpretation when systems are applied beyond their original context (Jeon et al., 2024). These limitations constrain the development of comprehensive architectural models that could inform best practices in precision beekeeping (Hadjur et al., 2022).

Based on these findings, future research directions should be closely aligned with the identified gaps. First, there is a clear need for robust field validation of integrated IoT–AI architectures across diverse ecological and operational contexts to assess their reliability and practical relevance (Guruprasad & Leiding, 2024; Kviesis et al., 2023). Second, interoperability remains a critical challenge, calling for standardized protocols and architectural frameworks that enable seamless data exchange and integration across heterogeneous systems (DeFranco et al., 2024). Third, emerging approaches such as federated intelligence warrant further investigation as mechanisms to enhance analytical robustness while preserving data locality and privacy across distributed beekeeping operations (Kaňovská, 2024). Collectively, these directions remain grounded in the architectural and system-level issues identified in the reviewed studies, rather than extending beyond the scope of the current evidence base.

Implications

From a theoretical perspective, the findings reinforce the importance of architecture-oriented frameworks in advancing precision beekeeping research. Treating integration depth as a core analytical construct shifts the focus from isolated component performance toward systemic interactions among sensing, communication, intelligence, and decision layers. This perspective supports the development of reference architectures that can be used to compare, evaluate, and refine emerging systems in a consistent and cumulative manner, as suggested in recent studies emphasizing structured architectural evaluation (Rafid et al., 2024).

From a practical standpoint, the literature indicates a growing consensus on the necessity of decision-oriented architectures in precision beekeeping. Studies increasingly emphasize that systems capable of supporting timely, context-aware decisions can enhance management efficiency and colony health, particularly when intelligence outputs are explicitly linked to actionable recommendations rather than passive monitoring interfaces (Alaieri, 2024; Alharbi & Aldossary, 2021; Jouini et al., 2024). Such architectures are especially relevant for UMKM-level beekeeping operations.

In this context, the adoption of reference architectures and standardized system designs can assist practitioners and system developers in selecting, adapting, and integrating IoT–AI solutions that align with practical constraints. By grounding decision-support mechanisms in coherent architectural frameworks, precision beekeeping systems can move beyond monitoring toward actionable, scalable, and context-sensitive solutions that remain consistent with the empirical evidence reported in the reviewed literature.

CONCLUSION AND SUGGESTIONS

Conclusion

Precision beekeeping fundamentally requires architectural integration across sensing, communication, intelligence, and decision layers. The architecture-oriented synthesis shows that existing IoT–AI beekeeping systems remain predominantly monitoring-centric, with strong emphasis on data acquisition and visualization, while systematic translation of analytical outputs into operational decisions is still limited. This imbalance reflects a structural and conceptual gap rather than a technological limitation, as current IoT and AI technologies are already capable of supporting deeper end-to-end integration.

Based on the synthesized evidence, this study positions the proposed architecture as a reference architecture for end-to-end smart beehive systems. This reference architecture is intended as an analytical and comparative framework to support system analysis and evaluation, rather than as a prescriptive blueprint for direct implementation. The reference architecture explicitly frames IoT–AI precision beekeeping as a decision-oriented system, where intelligence outputs are designed to support timely, context-aware actions rather than passive monitoring alone. This contribution advances precision beekeeping research toward coherent, decision-relevant system design, with particular relevance for UMKM-level beekeeping operations, defined in this study as micro, small, and medium-scale enterprises characterized by limited resources and high sensitivity to decision timeliness.

Suggestions

First, the proposed reference architecture should be adopted as a design guideline for developing future IoT–AI precision beekeeping systems. Emphasizing architectural coherence and explicit decision orientation can help shift system development from monitoring-centric implementations toward solutions that deliver actionable operational value. Second, the architectural logic derived from this study can be used as a comparative evaluation framework for assessing emerging precision beekeeping systems. Applying a shared architectural reference enables consistent evaluation of integration depth, decision relevance, and system maturity across studies, supporting cumulative knowledge building and more systematic advancement of the field.

REFERENCES

Abdollahi, M., Henry, E., Giovenazzo, P., & Falk, T. H. (2022). The Importance of Context Awareness in Acoustics-Based Automated Beehive Monitoring. Applied Sciences, 13(1), 195. https://doi.org/10.3390/app13010195

Alaieri, F. (2024). Precision Agriculture Based on Machine Learning and Remote Sensing Techniques. Engineering Technology & Applied Science Research, 14(3), 14206–14211. https://doi.org/10.48084/etasr.6986

Alharbi, H. A., & Aldossary, M. (2021). Energy-Efficient Edge-Fog-Cloud Architecture for IoT-Based Smart Agriculture Environment. Ieee Access, 9, 110480–110492. https://doi.org/10.1109/access.2021.3101397

Anwar, O., Keating, A., Cardell-Oliver, R., Datta, A., & Putrino, G. (2022). Design and development of low-power, long-range data acquisition system for beehives - BeeDAS. Computers and Electronics in Agriculture, 201, 107281. https://doi.org/10.1016/j.compag.2022.107281

Astuti, P. K., Hegedűs, B., Oleksa, A., Bagi, Z., & Kusza, S. (2024). Buzzing With Intelligence: Current Issues in Apiculture and the Role of Artificial Intelligence (AI) to Tackle It. Insects, 15(6), 418. https://doi.org/10.3390/insects15060418

Bartos, H., Bodor, Z., Keresztesi, Á., Gârbacea, G., Deák, G., Monica, M., Laslo, L., Boboc, M., Elena, H., & Szép, R. (2024). Advances in Beehive Monitoring Systems: Low-Cost Integrating Sensor Technology for Improved Apiculture Management. E3s Web of Conferences, 589, 04001. https://doi.org/10.1051/e3sconf/202458904001

Calderita, L. V, Vega, A., Barroso, S., Bustos, P., & Núñez, P. (2020). Designing a Cyber-Physical System for Ambient Assisted Living: A Use-Case Analysis for Social Robot Navigation in Caregiving Centers. Sensors, 20(14), 4005. https://doi.org/10.3390/s20144005

Catania, P., & Vallone, M. (2020). Application of a Precision Apiculture System to Monitor Honey Daily Production. Sensors, 20(7), 2012. https://doi.org/10.3390/s20072012

Cecchi, S., Spinsante, S., Terenzi, A., & Orcioni, S. (2020). A Smart Sensor-Based Measurement System for Advanced Bee Hive Monitoring. Sensors, 20(9), 2726. https://doi.org/10.3390/s20092726

Danieli, P. P., Addeo, N. F., Lazzari, F., Manganello, F., & Bovera, F. (2023). Precision Beekeeping Systems: State of the Art, Pros and Cons, and Their Application as Tools for Advancing the Beekeeping Sector. Animals, 14(1), 70. https://doi.org/10.3390/ani14010070

DeFranco, J. F., Roberts, J., Ferraiolo, D., & Compton, D. C. (2024). An Infrastructure for Secure Data Sharing: A Clinical Data Implementation. Jamia Open, 7(2). https://doi.org/10.1093/jamiaopen/ooae040

Doinea, M., Trandafir, I., Toma, C.-V., Popa, M., & Zamfiroiu, A. (2024). IoT Embedded Smart Monitoring System With Edge Machine Learning for Beehive Management. International Journal of Computers Communications & Control, 19(4). https://doi.org/10.15837/ijccc.2024.4.6632

Edwards-Murphy, F., Magno, M., O'Leary, L., Troy, K., Whelan, P., & Popovici, E. M. (2015). Big brother for bees (3B) - Energy neutral platform for remote monitoring of beehive imagery and sound. 2015 6th International Workshop on Advances in Sensors and Interfaces (IWASI), 106–111. https://doi.org/10.1109/IWASI.2015.7184943

Falcão, S. I., Bocquet, M., Chlebo, R., Barreira, J. C., Giacomelli, A., Škerl, M. I. S., & Quaglia, G. (2024). Composition and Quality of Honey Bee Feed: The Methodology and Monitoring of Candy Boards. Animals, 14(19), 2836. https://doi.org/10.3390/ani14192836

Faurot-Daniels, C., Glenny, W., Daughenbaugh, K. F., McMenamin, A. J., Burkle, L. A., & Flenniken, M. L. (2020). Longitudinal Monitoring of Honey Bee Colonies Reveals Dynamic Nature of Virus Abundance and Indicates a Negative Impact of Lake Sinai Virus 2 on Colony Health. Plos One, 15(9), e0237544. https://doi.org/10.1371/journal.pone.0237544

Gajger, I. T., Vlainić, J., Šoštarić, P., Prešern, J., Bubnič, J., & Škerl, M. I. S. (2020). Effects on Some Therapeutical, Biochemical, and Immunological Parameters of Honey Bee (Apis Mellifera) Exposed to Probiotic Treatments, in Field and Laboratory Conditions. Insects, 11(9), 638. https://doi.org/10.3390/insects11090638

Gil-Lebrero, S., Quiles-Latorre, F., Ortiz-López, M., Sánchez-Ruiz, V., Gámiz-López, V., & Luna-Rodríguez, J. (2017). Honey Bee Colonies Remote Monitoring System. Sensors, 17(1), 55. https://doi.org/10.3390/s17010055

Girotti, S., Ghini, S., Ferri, E. N., Bolelli, L., Colombo, R., Serra, G., Porrini, C., & Sangiorgi, S. (2020). Bioindicators and Biomonitoring: Honeybees and Hive Products as Pollution Impact Assessment Tools for the Mediterranean Area. Euro-Mediterranean Journal for Environmental Integration, 5(3). https://doi.org/10.1007/s41207-020-00204-9

Guo, Y., Diao, Q., Dai, P., Wang, Q., Hou, C., Liu, Y., Zhang, L., Luo, Q., Wu, Y., & Gao, J. (2021). The Effects of Exposure to Flupyradifurone on Survival, Development, and Foraging Activity of Honey Bees (Apis Mellifera L.) Under Field Conditions. Insects, 12(4), 357. https://doi.org/10.3390/insects12040357

Guruprasad, S. M., & Leiding, B. (2024). BeeOpen—An Open Data Sharing Ecosystem for Apiculture. Agriculture, 14(3), 470. https://doi.org/10.3390/agriculture14030470

Hadjur, H., Ammar, D., & Lefèvre, L. (2022). Toward an Intelligent and Efficient Beehive: A Survey of Precision Beekeeping Systems and Services. Computers and Electronics in Agriculture, 192, 106604. https://doi.org/10.1016/j.compag.2021.106604

Ho, I.-C., Lai, Y.-J., Chiang, P.-N., Chen, Y.-F., & Lin, T.-T. (2022). Integration of Multiple Sensors for Beehive Health Status Monitoring and Assessment. 2022 Houston, Texas July 17-20, 2022. https://doi.org/10.13031/aim.202200376

Huho, J. M., Ng'ang'a, I., Macharia, K., Mburu, L. N., & Stöber, S. (2024). Apicultural Knowledge for Ecological Sustainability, Food Security and Economic Empowerment. AfriTVET, 9(1), 56–64. https://doi.org/10.69641/afritvet.2024.91181

Javed, Y., Felemban, M., Shawly, T., Kobes, J., & Ghafoor, A. (2020). A Partition-Driven Integrated Security Architecture for Cyberphysical Systems. Computer, 53(3), 47–56. https://doi.org/10.1109/mc.2019.2914906

Jeon, K., Park, W. Y., Kahn, C. E., Nagy, P., You, S. C., & Yoon, S. H. (2024). Advancing Medical Imaging Research Through Standardization. Investigative Radiology, 60(1), 1–10. https://doi.org/10.1097/rli.0000000000001106

Jouini, O., Sethom, K., Namoun, A., Aljohani, N., Alanazi, M. H., & Alanazi, M. N. (2024). A Survey of Machine Learning in Edge Computing: Techniques, Frameworks, Applications, Issues, and Research Directions. Technologies, 12(6), 81. https://doi.org/10.3390/technologies12060081

Junior, N., Silva, A., Guelfi, A. E., Azevedo, M. T. d., & Kofuji, S. T. (2021). Lightweight and Secure Publish-Subscribe System for Cloud-Connected Ultra Low Power IoT Devices. Journal of Communication and Information Systems, 36(1), 110–113. https://doi.org/10.14209/jcis.2021.11

Kaňovská, L. (2024). The Use of Products With a Monitoring System for Remote Bee Detection in Beekeeping in Czechia. Agris On-Line Papers in Economics and Informatics, 16(1), 67–81. https://doi.org/10.7160/aol.2024.160106

Kontogiannis, S. (2024). Beehive Smart Detector Device for the Detection of Critical Conditions That Utilize Edge Device Computations and Deep Learning Inferences. Sensors, 24(16), 5444. https://doi.org/10.3390/s24165444

Kviesis, A., Komašilovs, V., Ozols, N., & Zacepins, A. (2023). Bee Colony Remote Monitoring Based on IoT Using ESP-NOW Protocol. Peerj Computer Science, 9, e1363. https://doi.org/10.7717/peerj-cs.1363

Magdin, M., Valovič, M., Koprda, Š., & Balogh, Z. (2020). Design and Realization of Interconnection of Multifunctional Weighing Device With Sigfox Data Network. Agris On-Line Papers in Economics and Informatics, 12(2), 99–110. https://doi.org/10.7160/aol.2020.120209

Matei, A., & Cocoşatu, M. (2024). Artificial Internet of Things, Sensor-Based Digital Twin Urban Computing Vision Algorithms, and Blockchain Cloud Networks in Sustainable Smart City Administration. Sustainability, 16(16), 6749. https://doi.org/10.3390/su16166749

McKinnon, A. C., Collins, L., Wood, J. L., Murphy, N., Franks, A. E., & Steinbauer, M. J. (2023). Precision Monitoring of Honey Bee (Hymenoptera: Apidae) Activity and Pollen Diversity During Pollination to Evaluate Colony Health. Insects, 14(1), 95. https://doi.org/10.3390/insects14010095

Meikle, W. G., Corby-Harris, V., Ricigliano, V., Snyder, L., & Weiss, M. (2023). Cold Storage as Part of a Varroa Management Strategy: Effects on Honey Bee Colony Performance, Mite Levels and Stress Biomarkers. Scientific Reports, 13(1). https://doi.org/10.1038/s41598-023-39095-5

Mezher, Z., Bubnič, J., Condoleo, R., Jannoni-Sebastianini, F., Leto, A., Proscia, F., & Formato, G. (2021). Conducting an International, Exploratory Survey to Collect Data on Honey Bee Disease Management and Control. Applied Sciences, 11(16), 7311. https://doi.org/10.3390/app11167311

Nilsson, A., D'Alvise, P., Milbrath, M. O., & Forsgren, E. (2024). Lactic Acid Bacteria in Swedish Honey Bees During Outbreaks of American Foulbrood. Ecology and Evolution, 14(2). https://doi.org/10.1002/ece3.10964

Novák, V., Stočes, M., Čížková, T., Jarolímek, J., & Kánská, E. (2021). Experimental Evaluation of the Availability of LoRaWAN Frequency Channels in the Czech Republic. Sensors, 21(3), 940. https://doi.org/10.3390/s21030940

Nsoh, B., Katimbo, A., Guo, H., Heeren, D. M., Nakabuye, H. N., Qiao, X., Ge, Y., Rudnick, D. R., Wanyama, J., Bwambale, E., & Kiraga, S. (2024). Internet of Things-Based Automated Solutions Utilizing Machine Learning for Smart and Real-Time Irrigation Management: A Review. Sensors, 24(23), 7480. https://doi.org/10.3390/s24237480

Ntawuzumunsi, E., Kumaran, S., Sibomana, L., & Mtonga, K. (2023). Design and Development of Energy Efficient Algorithm for Smart Beekeeping Device to Device Communication Based on Data Aggregation Techniques. Algorithms, 16(8), 367. https://doi.org/10.3390/a16080367

Potamitis, I. G., Rigakis, I. I., Psirofonia, G., Tzagaraki, E., & Alissandrakis, E. K. (2023). Co-Interpreting Vibrational Sensors, Gas And Environmental Parameters For Beehive Health Assessment. Proceedings of 29th International Congress on Sound and Vibration (ICSV29).

Progoulakis, I., Rohmeyer, P., & Никитакос, Н. (2021). Cyber Physical Systems Security for Maritime Assets. Journal of Marine Science and Engineering, 9(12), 1384. https://doi.org/10.3390/jmse9121384

Rafid, I., Findley, D. J., & Kim, K. S. (2024). Hydra-Ran Perceptual Networks Architecture: Dual-Functional Communications and Sensing Networks for 6G and Beyond. Ieee Access, 12, 2162–2185. https://doi.org/10.1109/access.2023.3341491

Robles-Guerrero, A., Gómez-Jiménez, S., Saucedo-Anaya, T., López-Betancur, D., Navarro-Solís, D. J., & Guerrero-Méndez, C. (2024). Convolutional Neural Networks for Real Time Classification of Beehive Acoustic Patterns on Constrained Devices. Sensors, 24(19), 6384. https://doi.org/10.3390/s24196384

Robles-Guerrero, A., Saucedo-Anaya, T., Guerrero-Méndez, C., Gómez-Jiménez, S., & Navarro-Solís, D. (2023). Comparative Study of Machine Learning Models for Bee Colony Acoustic Pattern

Classification on Low Computational Resources. Sensors, 23(1), 460. https://doi.org/10.3390/s23010460
Săcăleanu, D. I., Matache, M., Rosu, S. G., Florea, B., Manciu, I.-P., & Perișoară, L. A. (2024). IoT-Enhanced Decision Support System for Real-Time Greenhouse Microclimate Monitoring and Control. Technologies, 12(11), 230. https://doi.org/10.3390/technologies12110230
Terence, S., Immaculate, J., Raj, M. M. A., & Nadarajan, J. (2024). Systematic Review on Internet of Things in Smart Livestock Management Systems. Sustainability, 16(10), 4073. https://doi.org/10.3390/su16104073
Tulu, D., Aleme, M., Mengistu, G., Bogale, A., Bezabeh, A., & Mendesil, E. (2020). Improved Beekeeping Technology in Southwestern Ethiopia: Focus on Beekeepers' Perception, Adoption Rate, and Adoption Determinants. Cogent Food & Agriculture, 6(1), 1814070. https://doi.org/10.1080/23311932.2020.1814070
Underwood, R. M., Lawrence, B. L., Turley, N. E., Cambron-Kopco, L., Kietzman, P. M., Traver, B. E., & López-Uribe, M. M. (2023). A Longitudinal Experiment Demonstrates That Honey Bee Colonies Managed Organically Are as Healthy and Productive as Those Managed Conventionally. Scientific Reports, 13(1). https://doi.org/10.1038/s41598-023-32824-w
Utami, P., Hartanto, R., & Soesanti, I. (2022). A Brief Study of The Use of Pattern Recognition in Online Learning: Recommendation for Assessing Teaching Skills Automatically Online Based. Elinvo (Electronics, Informatics, and Vocational Education), 7(1), 48–62. https://doi.org/10.21831/elinvo.v7i1.51354
Wachowicz, A., Pytlik, J., Tokarz, K., & Mrozek, D. (2022). Edge Computing in IoT-enabled Honeybee Monitoring for the Detection of Varroa Destructor. International Journal of Applied Mathematics and Computer Science, 32(3). https://doi.org/10.34768/amcs-2022-0026
Zacepins, A., Kviesis, A., Pecka, A., & Osadcuks, V. (2017). Development of Internet of Things concept for Precision Beekeeping. 2017 18th International Carpathian Control Conference (ICCC), 23–27. https://doi.org/10.1109/CarpathianCC.2017.7970365
Zheng, Y., Cao, X., Xu, S., Guo, S., Huang, R., Li, Y., Chen, Y., Yang, L., Cao, X., Idrus, Z., & Sun, H. (2024). Intelligent beehive monitoring system based on internet of things and colony state analysis. Smart Agricultural Technology, 9, 100584. https://doi.org/10.1016/j.atech.2024.100584