

Precision Apiculture with Artificial Intelligence: A Survey of Methods, Tools, and Future Directions

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Abstract. Beekeeping plays a vital role in maintaining biodiversity, ecosystem balance, and global food security through pollination and the production of honey and other bee products. However, apiculture faces increasing threats from disease outbreaks, colony collapse disorder, and environmental stressors. In recent years, the convergence of artificial intelligence (AI), bio-inspired computation, and precision agriculture has introduced new tools for sustainable and intelligent beekeeping. This review aims to provide a comprehensive overview of AI applications in beekeeping, with an emphasis on both theoretical approaches and existing tools. It further explores the role of bio-inspired algorithms, such as the Artificial Bee Colony (ABC), in linking natural swarm behaviour to computational optimisation problems. The most prominent AI implementations are found in disease diagnostics, using Computer Vision (CV) and Deep Learning (DL) for the detection of pathogens such as *Varroa destructor* and *Nosema*. Behavioural tracking through video analytics and acoustic monitoring is gaining momentum, offering early warnings for colony stress and swarming. While commercial tools demonstrate practical feasibility, adoption remains uneven due to cost, infrastructure needs, and limited access among small-scale beekeepers. However, data scarcity and model generalisability remain significant limitations. The integration of AI and evolutionary computation into precision beekeeping presents a transformative opportunity to enhance sustainability, productivity, and resilience in apiculture. The interdisciplinary nature of intelligent apiculture opens up opportunities for collaboration across fields such as computer science, agriculture, ecology, and ethics. This study establishes a foundation for future research in AI-driven beekeeping, aligned with the goals of sustainable agriculture and environmental stewardship.

Key words: artificial intelligence, internet of things, machine learning, precision apiculture, precision beekeeping, smart agriculture.

Introduction

Beekeeping plays a crucial role in agriculture and biodiversity conservation, as pollinators are responsible for the reproduction of approximately 75% of flowering plants and nearly 35% of global food crops (United Nations, 2019). Additionally, beekeeping contributes to building herd immunity within ecosystems by maintaining stable bee populations (Filipczuk *et al.*, 2018). However, the decline of bee populations due to climate change, habitat loss, pesticide exposure, and disease outbreaks has raised significant global concerns, necessitating the development of innovative strategies to improve hive management and colony health. While traditional

beekeeping practices have been effective for centuries, they often lack precision, scalability, and adaptability to modern agricultural and environmental challenges.

The concept of Precision Beekeeping (PB) was first introduced in 2012 (Zacepins *et al.*, 2012) as a management strategy aimed at optimising beekeeping practices through the continuous monitoring of individual colonies. The primary goal of PB is to enhance colony productivity, minimise resource consumption, and improve long-term bee health. This approach involves collecting and analysing data related to hive conditions and colony behaviour. At the colony level, research focuses on internal organisation, bee lifecycle patterns, and the influence of external

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factors such as weather conditions. On a broader scale, monitoring multiple hives enables comprehensive apiary management, allowing beekeepers to make data-driven decisions.

The significance of PB has led to an expanding body of research covering various aspects of hive monitoring. Notable contributions include studies on temperature monitoring within colonies (Zacepins & Karasha, 2013), advancements in data collection and smart beekeeping technologies (Marchal *et al.*, 2020), sound analysis for colony health assessment (Terenzi *et al.*, 2020), and predictions on the future trajectory of PB applications (Bumanis, 2020). A systematic review of the literature indicates that key research efforts focus on weight monitoring, internal temperature and humidity regulation, acoustic analysis, bee counting, and environmental condition sensing (Marchal *et al.*, 2020; Danieli *et al.*, 2023; Milovanovic *et al.*, 2023). As the size and cost of electronic sensors continue to decrease while their precision and capacity improve, continuous monitoring of hive variables such as weight, temperature, humidity, gases, sound, and bee traffic has become increasingly feasible. Researchers are now exploring multi-sensor fusion techniques to analyse complex datasets and extract phenological and behavioural insights without disturbing the colony. This evolution underscores the growing importance of integrated, non-invasive monitoring approaches as foundational tools in precision beekeeping (Meikle, Weiss & Ricigliano, 2025).

Beekeeping has been an integral part of human civilisation for millennia, evolving from rudimentary hive product collection methods to sophisticated modern apiculture. Throughout history, humans have relied on bees not only for honey but also for wax, medicinal applications, and, most importantly, their role in pollination. As agricultural demands have increased, traditional methods of beekeeping have faced numerous challenges, including colony losses, environmental changes (Abrol, 1992), mite infestation (Ziegelmann *et al.*, 2018; Hillayová *et al.*, 2022), attack of predators (Requier *et al.*, 2019), and the rise of pests and diseases. These challenges have driven the development of modern, technology-assisted beekeeping techniques, collectively known as Smart Apiculture (SA). While these innovations offer promising solutions to improve hive management, optimise productivity, and protect bee populations, they also introduce new risks and ethical considerations. The integration of AI into beekeeping introduces a transformative potential for real-time hive monitoring, behavioural pattern recognition, and environmental assessment. Technologies such as Machine Learning (ML), Computer Vision (CV), and the Internet of Things (IoT) enable automated data collection and

analysis, reducing labour intensity while enhancing colony health management. This paper explores the applications of AI in modern apiculture, categorising its impact into three principal domains: colony health monitoring, environmental analysis, and pollination optimisation.

From Traditional Beekeeping to Smart Apiculture

The origins of beekeeping can be traced back at least 4,500 years, with some of the earliest evidence found in ancient Egyptian hieroglyphs depicting honey collection and hive management. In these early systems, beekeepers primarily harvested honey from wild colonies or used rudimentary hives made of clay or hollowed-out logs. Over time, various civilisations, including the Greeks and Romans, refined hive construction techniques, introducing woven straw skeps and wooden boxes to facilitate honey collection. Despite these advancements, traditional beekeeping remained largely dependent on natural swarming behaviours, offering limited control over colony health and productivity (Crane, 1999). While traditional methods provided a sustainable means of honey production for centuries, they came with significant limitations. One of the major drawbacks was the lack of standardised hive designs, which often led to colony destruction during honey harvesting. Additionally, beekeepers only had basic tools to monitor colony health, making it difficult to detect early signs of disease or stress. However, these methods are often time-consuming, labour-intensive, and susceptible to human error (Langstroth, 2004). External threats, such as habitat destruction, pesticide use, and climate change, further exacerbated colony losses. The introduction of parasitic mites, such as *Varroa destructor* – first observed in *Apis Mellifera* families in 1950 in Asia, from where it spread to the USA and Europe – in the 20th century led to severe declines in bee populations, necessitating more advanced intervention methods (Ziegelmann *et al.*, 2018; Hillayová *et al.*, 2022).

Modern apiculture owes much to the work of Reverend Langstroth in 1851. He took a number of existing ideas and transformed them into a more managed system, which led to the development of the movable frame hive, allowing beekeepers to alter and manipulate the workings of the colony for their own advantage (see Figure 1). The movable frame of the hive and the concept of a movable comb were based on an understanding of bee space – the space required for two bees to pass each other back-to-back. The emergence of the Langstroth hive in the mid-19th century revolutionised beekeeping, allowing for non-destructive honey extraction and improved hive inspections. This marked the beginning of systematic colony management, which was further



Figure 1. Apipol hive – type of hive based on Langstroth with a movable frame.

enhanced by the development of disease treatments, selective breeding programmes, and improved feeding strategies. However, despite these advances, beekeepers still faced challenges in monitoring large-scale operations and responding to environmental fluctuations in real time.

The emergence of precision agriculture has revolutionised farming (Whelan and Taylor, 2013) through the integration of modern technology such as AI, IoT, and Big Data analytics. In beekeeping, these technologies have introduced innovative ways to monitor hive conditions remotely, detect early signs of disease, and optimise pollination efficiency. In recent years, sensor-based technologies have been widely used in hive monitoring (Meikle and Holst, 2015; Marchal *et al.*, 2019; Zaman and Dorin, 2023). Smart hives equipped with temperature, humidity, and acoustic sensors now provide real-time data on colony health, enabling beekeepers to take proactive measures to prevent colony collapse (Alleri *et al.*, 2023; Danieli *et al.*, 2023). ML algorithms can analyse bee behaviour patterns to detect anomalies, while CV systems assist in monitoring hive entrances and assessing population dynamics. These technological innovations enhance beekeeping efficiency by reducing manual labour, minimising losses, and optimising pollination services in agricultural settings. Moreover, AI-driven models can analyse vast amounts of data, identify patterns,

and generate predictive insights that improve decision-making and hive management strategies.

Despite the promising benefits of SA, the integration of technology into beekeeping also raises some concerns. The reliance solely on electronic monitoring systems may create challenges related to equipment failures, sensor inaccuracies, and overdependence on automated decision-support systems. While precision beekeeping technologies provide valuable real-time data, they may not fully replace the experiential knowledge of beekeepers, particularly in interpreting complex colony behaviours and environmental interactions. Additionally, large-scale commercial beekeeping operations may contribute to genetic homogenisation through the widespread use of selectively bred bee strains optimised for productivity. Although precision beekeeping technologies themselves are not inherently linked to biodiversity loss, their adoption within industrialised systems may reinforce management practices that favour uniform, highly productive colonies. There is also an ongoing debate about the ethical implications of manipulating bee behaviour through artificial means, as excessive intervention could disrupt natural colony dynamics.

AI and Evolutionary Algorithms in Precision Beekeeping

The integration of AI into beekeeping represents a significant advancement in PA, enabling real-

time monitoring, data-driven decision-making, and proactive hive management. Traditional beekeeping methods, while effective, often rely on manual inspections and subjective assessments, which can be time-consuming and prone to human error. AI-driven technologies offer a transformative approach, leveraging image analysis, acoustic monitoring, sensor data, and predictive modelling to enhance colony health, optimise colony productivity, and improve environmental analysis for sustainable beekeeping. This chapter explores the key applications of AI in modern beekeeping. Hive Condition Monitoring examines how AI can be used to detect diseases, assess colony behaviour, and regulate environmental conditions.

Colony Health Monitoring and Disease Detection

One of the most critical aspects of beekeeping is ensuring colony health and early disease detection. AI-powered solutions utilise CV, Deep Learning (DL), and sound analysis to monitor hive conditions and detect potential threats. Image and video recognition algorithms can identify symptoms of diseases such as Varroa mite infestations or Nosema infections, allowing beekeepers to intervene promptly. Additionally, acoustic sensors can detect abnormal colony activity, such as queen loss or swarming behaviour, providing real-time alerts. Maintaining colony health is a fundamental aspect of beekeeping, as disease outbreaks, environmental stressors, and colony disorders can lead to significant bee losses. The application of AI has the potential to revolutionise colony health management by enabling continuous, automated, and highly accurate diagnostics.

Computer Vision for Disease Diagnosis

The application of AI-driven image and video analysis in beekeeping has revolutionised colony health monitoring, offering non-invasive, real-time diagnostics for detecting diseases, monitoring colony behaviour, and assessing environmental stressors. By

leveraging CV, DL, and automated image processing, AI enhances the precision and efficiency of disease identification, enabling beekeepers to take proactive measures.

Computer Vision for Disease Diagnosis

Computer vision, a branch of AI focused on automated image interpretation, plays a crucial role in detecting pathogens, parasites, and abnormalities in honeybee colonies. Traditional disease detection methods require manual inspections and laboratory tests, which are time-consuming and often stressful for the colony. AI-driven CV significantly reduces these challenges by automating the detection process (see Figure 2). AI trained on large datasets of bee images can accurately identify symptoms of common threats, such as:

- **Varroa destructor mite infestation** – One of the most destructive threats to honeybee colonies is the Varroa destructor mite, which is a parasite that attaches itself to bees and spreads viruses, weakening or killing entire colonies (Warner *et al.*, 2024). By continuously scanning images captured from hives, AI-driven tools can minimise manual labour and enable early intervention to prevent colony collapse.
- **Nosema spores detection** – Nosema is a fungal pathogen that affects the digestive tracts of bees, leading to colony weakness and increased mortality rates (Duquesne *et al.*, 2021). Traditionally, Nosema detection requires the microscopic examination of bee samples. However, AI-driven image processing can enhance the speed and accuracy of diagnosis. AI-assisted microscopy combined with image recognition models can differentiate infected bee samples. This method allows for faster, large-scale screening of colonies, helping beekeepers make timely treatment decisions.

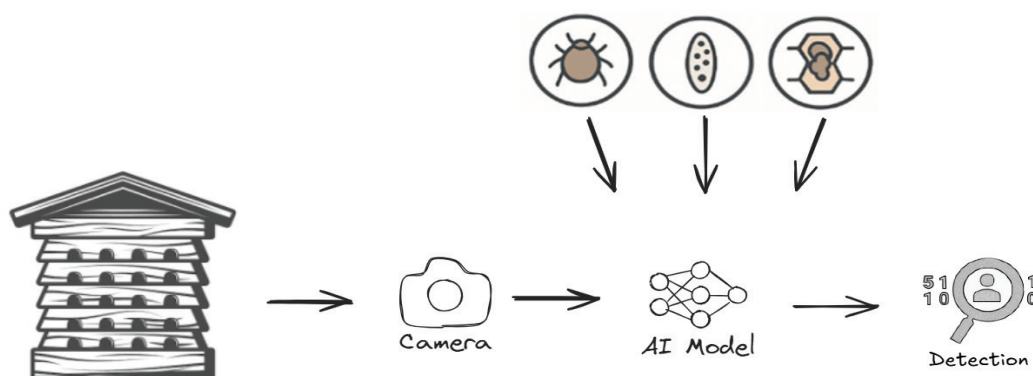


Figure 2. Computer vision for disease diagnosis in beekeeping.

- **American and European foulbrood** – American foulbrood (AFB) and European foulbrood (EFB) are bacterial infections that devastate bee larvae, leading to widespread colony losses (Hesketh-Best et al., 2024). AI-based image recognition models analyse photographs of brood combs to detect early symptoms, including discoloured, sunken, perforated cells or irregularities in larvae.

Automated Beehive Monitoring via Video Analysis

AI-powered video analysis enhances colony health monitoring by continuously tracking bee behaviour, activity levels, and colony conditions. Advanced CV models extract and interpret motion patterns, interactions, and anomalies that indicate potential health issues (see Figure 3). Modern AI systems utilise high-resolution cameras mounted inside and outside hives to analyse bee behaviour and identify abnormalities. These systems employ:

- **Object detection models** – monitoring individual bees within the hive is challenging due to their small size, rapid movements, and the densely populated environment. AI models trained in object detection and tracking help analyse bee behaviour in video feeds. By continuously analysing video feeds, these AI tools detect early warning signs of colony stress, allowing for timely interventions.
- **Anomaly detection algorithms** – unusual bee movement patterns often indicate disease, pesticide exposure, or environmental stress. AI-based unsupervised learning techniques help identify behavioural anomalies in colonies. By identifying subtle deviations in activity levels, these AI models allow beekeepers to intervene before colony health deteriorates.
- **Behavioural clustering models** – AI-driven behavioural clustering segments colony activity

into different functional zones, providing insights into colony health. These approaches provide beekeepers with a comprehensive view of hive dynamics, aiding in predictive health management.

Real-time analysis of video feeds allows beekeepers to respond swiftly to emerging threats, reducing colony losses.

Existing Commercial Solutions

In recent years, several commercial and open solutions using AI to analyse images of beehives and bees have been created:

- **BeeScanning** (<https://www.beescanning.com/>) – a mobile application that uses image recognition algorithms to detect Varroa destructor parasites based on photos taken with a smartphone. The system is based on DL models that classify and localise mites on bees' bodies.
- **Beewise AG** (<https://beewise.ag/>) – a solution that uses AI-powered CV to count bees and analyse frame images, down to individual cells, and then alerts beekeepers to any issues.
- **Bee sensing** (<http://bee-sensing.com/>) – the system sets beekeepers free from frequently patrolling their bee boxes by using IoT AI, or mobile sensors and smartphone apps supported by cloud AI.
- **DeepBee** (<https://github.com/avsthiago/DeepBee>) – a research project developing AI models to classify anomalies in bee behaviour based on video recordings.

AI Models Used in Image and Video Analysis

The following AI models are used to effectively analyse images and video recordings from beehives:

- **Convolutional Neural Networks (CNNs)** – convolutional networks such as ResNet, EfficientNet or MobileNet are ideal for image

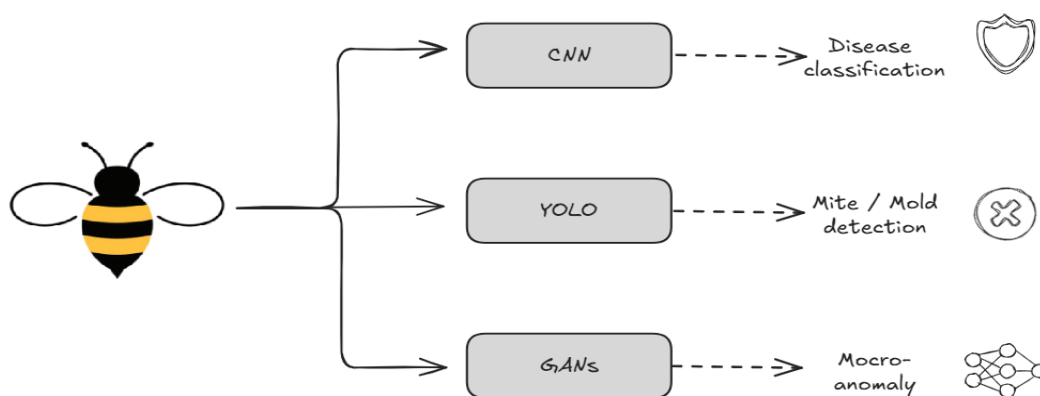


Figure 3. AI models for beehive image and video analysis.

classification and disease detection based on bee and honeycomb photographs. CNNs can be used to identify Varroa destructor, Nosemosis or wing deformation caused by the Deformed Wing Virus (DWV).

- **Object Detection Models (YOLO, Faster R-CNN, SSD)** – object detection algorithms allow for the localisation of specific threats in images, e.g., the presence of Varroa mites on bees, or areas of mouldy comb. YOLO (You Only Look Once) enables ultra-fast analysis in real time, making it ideal for monitoring beehives with cameras.
- **Transformers for Image Analysis (ViT – Vision Transformers)** – modern models such as Vision Transformer allow for the more accurate structural analysis of the image, which can help detect micro-anomalies in bee tissues or honeycombs.
- **Generative Adversarial Networks (GANs) for Data Augmentation** – GANs can be used to generate synthetic images of sick bees, allowing for the more effective training of AI models, even with limited real-world data.

Potential Applications and the Future of Technology

Automatic image and video analysis opens up new possibilities in the field of:

- **Fast and low-cost disease detection** – instead of time-consuming and expensive laboratory tests, beekeepers can preliminarily diagnose colonies using AI applications.
- **Monitoring the health of colonies on a large scale** – AI systems can process images from many hives simultaneously, which is crucial for commercial apiaries.
- **Integration with IoT systems** – cameras and sensors in the hive can continuously collect data, which is then analysed in the cloud by AI models, automatically generating alerts when a threat is detected.

In the coming years, the development of AI algorithms and the increased availability of cheap cameras and drones will enable even more accurate image analysis, which could significantly improve the protection of bee populations around the world.

Acoustic and Behavioural Analysis

AI-driven acoustic monitoring and pattern recognition are emerging as powerful tools for

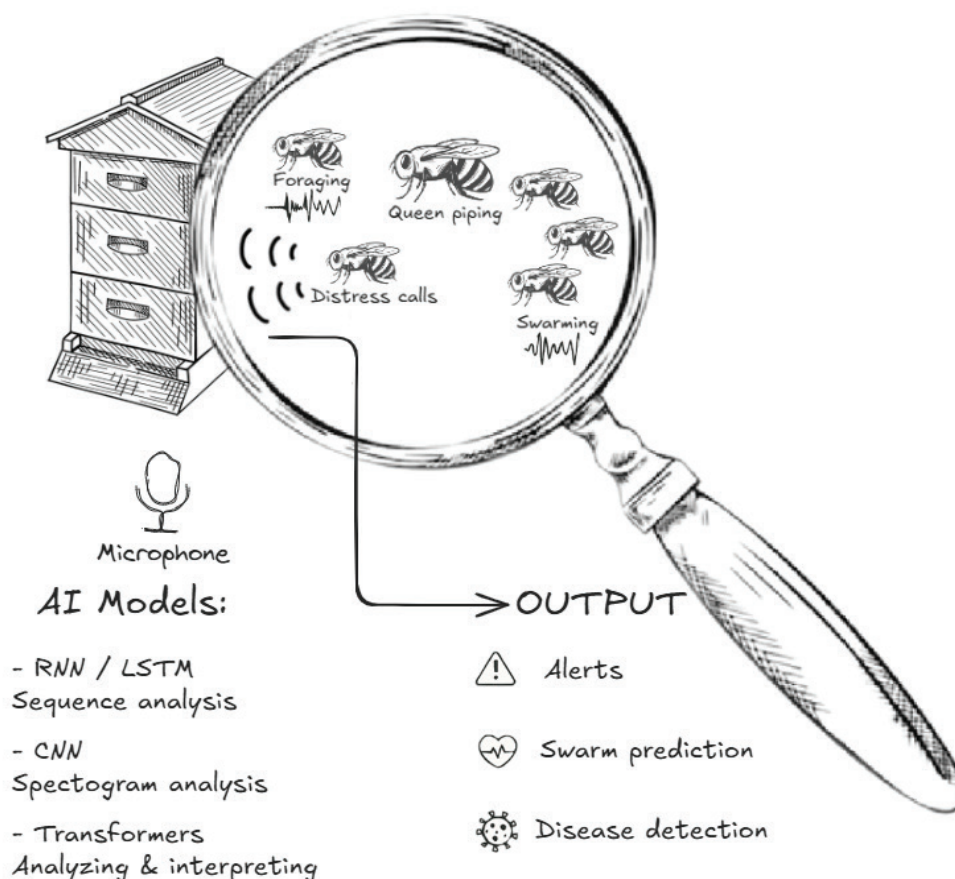


Figure 4. AI-driven acoustic and behavioural analysis in beekeeping.

assessing colony health, detecting diseases, and identifying colony stress factors without invasive inspections. By analysing the frequency, intensity, and patterns of sounds produced by bees, AI algorithms can extract meaningful insights regarding colony vitality, queen status, swarming tendencies, and disease presence (see Figure 4).

Bees communicate using vibrations and sound patterns, making acoustic monitoring a powerful tool for colony health diagnostics. AI models trained in speech and sound recognition analyse hive audio data to detect bees' communication, which can be categorised into the following patterns:

- **Foraging Sounds:** Worker bees produce distinct low-frequency buzzing when gathering nectar and pollen (Ferreira *et al.*, 2023).
- **Queen Piping:** A high-pitched sound made by virgin or mated queens, often preceding swarming or supersedure events (Uthoff *et al.*, 2023).
- **Worker and Drone Buzzing:** The frequency and intensity of wing beats indicate bee activity levels and colony stress factors (Cecchi *et al.*, 2019).
- **Distress Calls:** When bees are under threat, such as exposure to pesticides, diseases, or predators, they emit characteristic distress sounds.

By analysing these sounds, AI models can detect subtle changes in hive activity, allowing for early intervention. AI-powered acoustic monitoring employs machine learning classifiers (Random Forest, Support Vector Machines, Deep Neural Networks) to categorise sound patterns and issue alerts for potential colony health issues.

Existing Commercial Solutions

The development of AI technology has facilitated the creation of several acoustic monitoring systems that support beekeepers in diagnosing colonies:

- **Bee Health Guru** (<https://www.beehealth.guru/>) – an application based on AI, using microphones placed in the hive (built-in microphone in the smartphone) to record and analyse sounds. The AI model classifies the collected sound signals, identifying, among others, Nosema infections, stress caused by a lack of food, and preparation for a swarm.
- **ApisProtect** – an advanced IoT system integrating acoustic, temperature and humidity sensors, analysing the condition of the colony in real time and sending alerts to beekeepers when disturbing changes are detected.
- **BeePi** (<https://github.com/VKEDCO/PYPL/tree/master/beepi>) – an open-source project combining microphones, cameras and sensors

to monitor bee activity in the hive and their flight behaviour. The use of machine learning algorithms allows for the identification of irregularities based on acoustic analysis.

AI Models Used in Sound Analysis

Various AI models are used to effectively recognise sound patterns in recordings from the hives:

- **Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM)** – neural networks designed to process sequential data, which are useful in real-time sound analysis. These models can recognise differences in the frequency and amplitude of sounds in a bee colony, allowing symptoms of stress or disease to be detected.
- **Convolutional Neural Networks (CNNs) for Spectrogram Analysis** – Convolutional networks are used to analyse spectrograms, or graphical representations of sounds. This technique enables the classification of recordings and the identification of specific sound anomalies, such as changes in buzzing caused by the presence of parasites (e.g., Varroa destructor).
- **Transformers (Wav2Vec, Whisper)** – modern audio signal processing models that learn from raw audio recordings. These models can analyse subtle changes in the acoustics of the hive and predict potential threats.
- **Hidden Markov Models (HMM)** – algorithms utilised to analyse changing sound patterns over time. They are used to detect changes in colony behaviour, such as an increase in noise in preparation for a swarm.

Potential Applications and the Future of Technology

Acoustic monitoring combined with AI opens up new possibilities in the field of:

- **Early disease detection** – sound analysis allows for the identification of changes in the colony, even before visible disease symptoms appear.
- **Swarm prediction** – sound patterns change as the colony prepares to divide. AI can predict these changes and warn beekeepers.
- **Monitoring the level of stress of bees** – hive sounds can reflect stress caused by, among others, a lack of food, extreme temperatures, or the presence of predators.
- **Automatic alerting of beekeepers** – AI systems can generate notifications based on detected sound anomalies, enabling a faster response to threats.

In the future, AI algorithms will become increasingly precise, and the development of cheap audio sensors will enable large-scale implementation

of acoustic monitoring, supporting the protection of bee populations and the effective management of apiaries.

Monitoring Sensor Data

Maintaining optimal temperature and humidity levels within a beehive is crucial for colony health, brood development, and honey production. Bees regulate their hive's internal conditions through ventilation, clustering, and water collection, but environmental fluctuations, climate change, and disease can disrupt this balance. AI-driven temperature and humidity monitoring provides beekeepers with real-time insights and predictive analytics to maintain a stable hive environment (see Figure 5). AI-enhanced IoT-based sensor networks collect real-time environmental data, which is processed using predictive analytics and reinforcement learning models to:

- **Detect overheating or chilling events** – The optimal brood temperature is 34–36 °C; deviations can hinder larval development and weaken the colony. Cold stress (<30 °C) slows metabolic rates, reducing activity and survival rates. Overheating (>40 °C) can cause colony collapse due to dehydration and wax melting (Abou-Shaara *et al.*, 2017).
- **Detect hive ventilation problems** – Optimal humidity levels range from 50–70% for brood incubation and honey ripening. Excess humidity (>80%) promotes fungal growth (chalkbrood, Nosema) and weakens bees. Low humidity (<40%) causes dehydration and disrupts honey preservation (Abou-Shaara *et al.*, 2017).

AI algorithms process raw sensor data to identify key environmental patterns. Statistical Analysis – detects daily fluctuations and seasonal trends; Time-Series Analysis – examines correlations between hive activity and climate changes, and anomaly detection – identifies abrupt temperature drops (indicating queen loss or disease). Recent advancements in Edge AI enable on-device processing of hive sensor data, reducing dependency on cloud computing and enhancing real-time decision-making.

Existing Commercial Solutions

Modern hive monitoring systems increasingly use temperature and humidity sensors that collect data in real time. Examples of existing technologies include:

- **BroodMinder** (<https://broodminder.com/>) – an advanced IoT system that uses temperature and humidity sensors that record data in real time and send it to a mobile app. AI analyses trends, detecting potential problems, such as sudden drops in temperature that signal a weakened colony.
- **HiveMind** – a platform integrating various sensors (including temperature, humidity, and hive weight), using machine learning algorithms to predict changes in the condition of the colony and warn beekeepers about threats.

AI Models Used in Temperature and Humidity Analysis

Various AI models are used to effectively analyse and predict changes in the hive environment:

- **Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM)** – used to analyse time series of temperature and humidity data. These models allow the

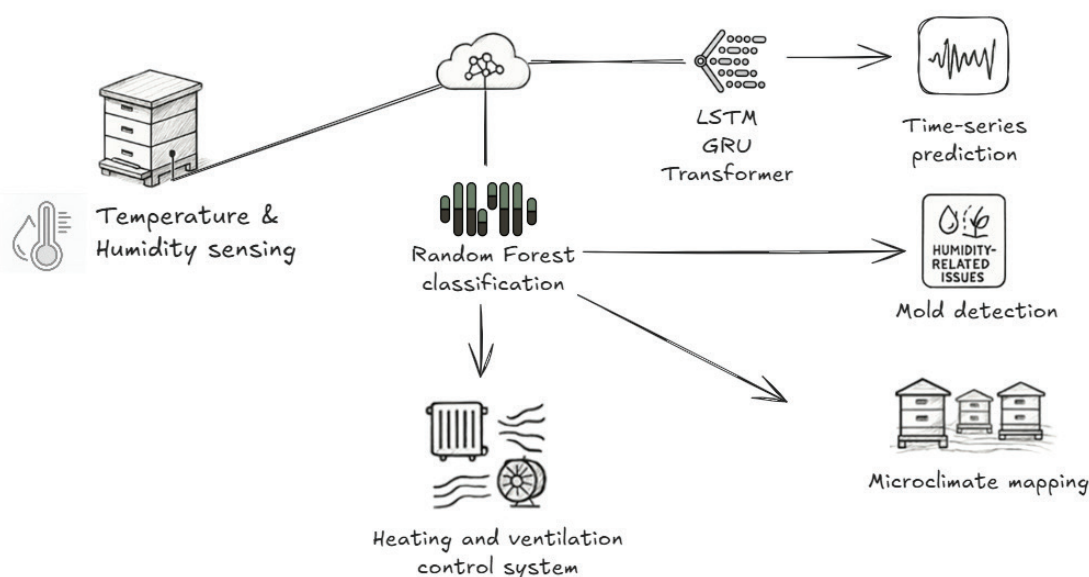


Figure 5. AI-driven monitoring of parameters inside the hive.

prediction of future changes in the hive based on previous trends, meaning beekeepers can proactively manage the apiary.

- **Random Forest and Gradient Boosting Machines (GBM)** – machine learning algorithms used to classify conditions in the hive and predict potential threats. They allow one to determine whether the colony is in optimal condition or requires intervention.
- **Bayesian Networks** – used to model the relationships between different environmental parameters. They allow one to predict the impact of changes in temperature and humidity on the behaviour and health of bees.
- **Transformers (Time Series Forecasting Models)** – advanced DL models that enable the long-term prediction of conditions in the hive and their impact on colony development.

AI Applications in Monitoring Temperature and Humidity

AI can be used in many aspects of hive management:

- **Early detection of diseases and colony weakness:**
 - A drop in temperature in the brood area can signal a problem with the queen bee or a decrease in the population of bees caring for larvae.
 - An increase in humidity can promote the development of moulds and infections, such as Nosema, which weaken the colony.
- **Optimisation of internal conditions**
 - Beekeepers can use AI analyses to adjust the positioning of hives, their insulation and ventilation to ensure optimal conditions for colony development throughout the year.
 - AI can predict critical moments, e.g., the need for additional heating of the hive in winter or improved ventilation in summer.
- **Prediction of bee behaviour**
 - AI models can analyse the temperature of the hive and predict when bees will start to increase their activity, which allows for planning activities related to honey harvesting or moving hives to the right places.
 - Based on data from different hives, it is possible to create microclimate maps and predict which colonies will develop better in a given region.
- **Minimising the risk associated with extreme weather conditions**
 - AI can analyse weather data in combination with conditions in the hive and warn beekeepers about threats such as heat waves

or sudden drops in temperature that can weaken the colony.

The Future of AI Technology in Monitoring Temperature and Humidity

The development of IoT sensors and the increasing availability of AI models will allow for the further optimisation of methods of monitoring hives. In the future, we can expect:

- **Increased automation** – AI systems will automatically regulate ventilation and heating of hives based on predicted weather conditions and the condition of the colony.
- **Greater precision of predictions** – thanks to increasingly accurate AI models, it will be possible to predict problems in colonies weeks before they actually occur.
- **Integration with global databases** – AI will analyse conditions in multiple apiaries simultaneously, providing beekeepers with recommendations based on a broad ecological and climatic context.

In summary, the use of temperature and humidity sensors combined with AI is a step towards more precise and efficient beekeeping. These systems allow for the early detection of threats, optimisation of conditions in the hive, and better management of colony health, which in the long term may contribute to halting the decline of the global bee population.

Predictive Bee Colony Health Analytics

Bee colony health is a dynamic and multidimensional system that is influenced by both internal biological factors and external environmental conditions. Early detection of health problems in beehives is one of the greatest challenges of modern beekeeping. Traditional methods of assessing the condition of colonies primarily rely on periodic visual inspections and the intuition of experienced beekeepers. However, such an approach is subjective, time-consuming, and often does not allow one to detect the first symptoms of diseases, stress or other threats before they begin causing irreversible consequences for bees. However, the development of AI and ML methods opens up new possibilities for predicting health threats in real time, before they become critical. AI is able to analyse huge amounts of data that may indicate early signs of stress and diseases in bee colonies (see Figure 6).

Machine learning models can:

- **Detect anomalies in colony behaviour** – analysis of historical data on bee movement, activity level, and sounds in the hive allows for the detection of deviations from the norm.
- **Identify hidden correlations between the environment and bee health** – AI algorithms can analyse factors such as temperature, humidity, CO₂ levels, and satellite data on

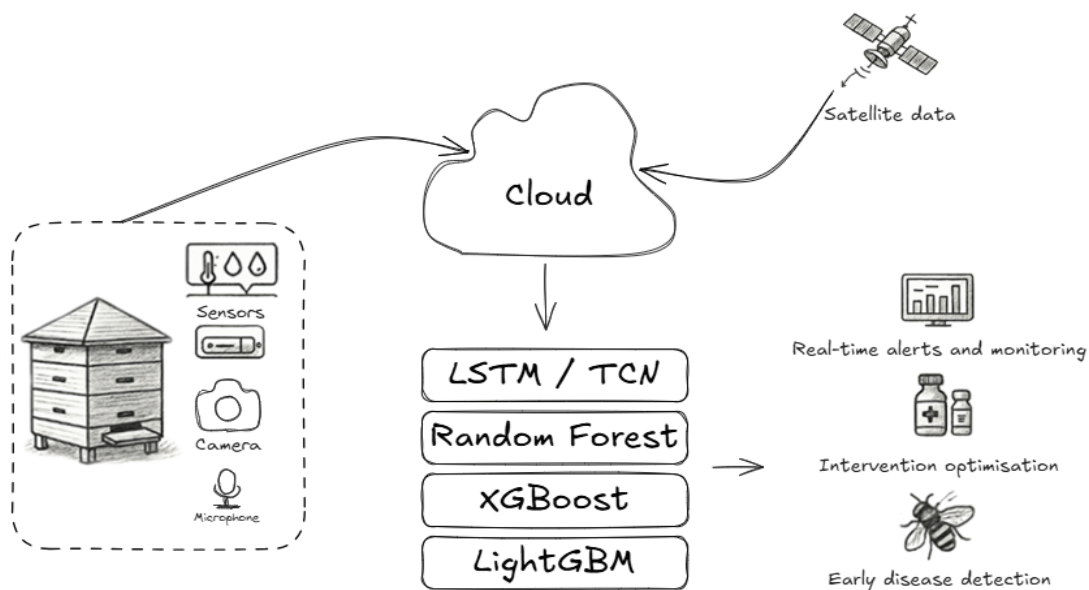


Figure 6. Predictive bee colony health analytics.

plant availability, and combine them with bee activity levels.

- **Predict future threats** – ML can analyse long-term trends and detect patterns that lead to problems such as Colony Collapse Disorder (CCD).

AI works much more precisely and quickly than traditional monitoring methods, enabling the automatic identification of threats and preventive action to be taken before the situation gets out of control. Only now, after defining the problem and discussing its essence, can we move on to describing specific AI models and their application in analysing bee colony health.

Existing Commercial Solutions

Predictive analysis of the health of the hive is based on the integration of various data sources: images and video recordings, sounds, microclimatic conditions and information about the external environment. Tools using ML include both commercial solutions and open-source systems.

Examples of existing systems and technologies:

- **Beewise AG** (<https://beewise.ag/>) – an advanced hive equipped with IoT sensors and ML algorithms that analyse the condition of the colony in real time. This system detects potential threats and autonomously adjusts internal conditions (e.g., ventilation).
- **BeeHiveMonitoring** (<https://beehivemonitoring.com/>) – a platform that collects data on temperature, humidity and bee activity, using ML models to predict changes in colony behaviour and prevent health problems.

Machine Learning Models Used in Colony Health Analysis

To predict changes in colony health, various ML models are used that enable temporal analysis, anomaly detection, and classification of hive states.

1. Models for time series analysis

Predicting colony health requires the analysis of long-term data, which is why models dedicated to time series analysis are used:

- **Long Short-Term Memory (LSTM)** – recurrent networks that enable the analysis of long-term dependencies in data, e.g., seasonal changes in temperature or bee population.
- **Temporal Convolutional Networks (TCN)** – modern alternative models to LSTM that offer better scalability and performance in the analysis of large data sets from IoT sensors.
- **Facebook Prophet** – a model used to analyse trends in colony health, e.g., predicting a decline in bee numbers or detecting seasonal cycles of hive development.

2. Anomaly detection models

To identify early signals of health problems, algorithms that detect anomalies in data are used:

- **Autoencoders** – neural networks that learn “normal” patterns of colony behaviour and detect deviations that suggest health problems.
- **Isolation Forest** – a model based on decision trees, effectively detecting rare and unusual events, e.g., a sudden collapse of hive activity.
- **One-Class SVM** – an algorithm that classifies the condition of the hive based on deviations from the standard pattern of a healthy colony.

3. Classification and regression models

To predict specific health problems, classification and regression models are used:

- **Random Forest** – an effective classification method used to identify the condition of the colony based on a set of features (temperature, humidity, activity).
- **XGBoost and LightGBM** – boosting algorithms used to predict the scale of health problems and their impact on hive productivity.
- **Multi-Layer Perceptron (MLP)** – classic neural networks that can combine data from different sources (e.g., images, sounds, sensors) to more accurately assess the health of the hive.

Application of AI Models in Practice

ML models can be used in several key areas of the predictive analysis of colony health:

- **Early detection of diseases and colony weakness**
 - Anomaly detection algorithms can identify early symptoms of diseases such as Nosema or Varroa destructor infestation before the problem becomes critical.
 - Classification models predict the likelihood of health problems based on historical trends and current measurements.
- **Optimising beekeeper interventions**
 - AI can suggest the best times to intervene, such as feeding supplements or using antiparasitic agents.
 - Predictive algorithms can indicate which hives require more attention, optimising beekeeper work time.
- **Predicting colony lifecycle**
 - ML models allow for the long-term planning of operations, predicting population growth, peak honey production, and risk periods for colonies.
 - LSTM and TCN can analyse long-term relationships in data, predicting the impact of climate and environmental changes on colony development.
- **Automatic reporting and recommendations**
 - Intelligent systems can generate colony health reports and propose specific actions, eliminating the need for manual data analysis.
 - AI can also send alerts about threats in real time, allowing beekeepers to react quickly.

The Future of Predictive Colony Health Analysis

As AI technology advances, predicting the health of bee colonies will become increasingly accurate. We can expect:

- **Integration with external data** – models will incorporate meteorological data and climate change into their predictions of colony health.

- **Personalisation of models** – algorithms will adapt to specific local conditions and the unique characteristics of each colony.
- **Greater automation** – future AI systems can not only predict threats but also take autonomous preventive actions.

ML is a breakthrough in monitoring bee health, allowing for the precise prediction of problems and optimisation of beekeeper interventions. Models such as LSTM, Random Forest or Autoencoders enable the analysis of a wide range of data, providing a better understanding of the processes taking place in the hive. In the future, AI may become a key tool in the fight against the decline of the bee population, contributing to the sustainable development of beekeeping.

Colony Dynamics and Productivity

Tracking bee behaviour and hive productivity is essential for optimising colony management. AI-powered tracking systems use different tools and techniques to monitor bee activity levels, movement patterns, and hive traffic. Predictive analytics models assess honey production rates, allowing beekeepers to adjust hive management strategies accordingly. These advancements contribute to data-driven decision-making, enhancing efficiency and sustainability in beekeeping.

The study of bee behaviour is essential for understanding colony health, productivity, and overall hive efficiency. Traditionally, beekeepers have relied on direct observations to assess colony strength, queen activity, and foraging patterns. However, manual monitoring is limited in scope and may not capture the full complexity of bee interactions within the hive. AI introduces new possibilities for tracking bee movements, predicting productivity, and automating key aspects of beekeeping. One of the most innovative applications of AI in behavioural analysis is tracking bee movement using CV and DL algorithms. By analysing video footage from inside the hive, AI can identify individual bees, monitor their interactions, and detect abnormalities in foraging behaviour. This information helps beekeepers understand colony dynamics and identify potential issues, such as queen failure or workforce imbalances. In addition to behavioural tracking, AI is also used for the predictive modelling of honey production. By integrating data from multiple sources – such as weather conditions, floral resource availability, and hive activity – ML models can estimate honey yields and predict colony growth trends. These predictive tools enable beekeepers to optimise hive placement, anticipate resource needs, and improve overall productivity. Furthermore, AI-driven automation is transforming hive management by reducing the need for manual interventions. Automated systems, including robotic beekeepers, smart feeding

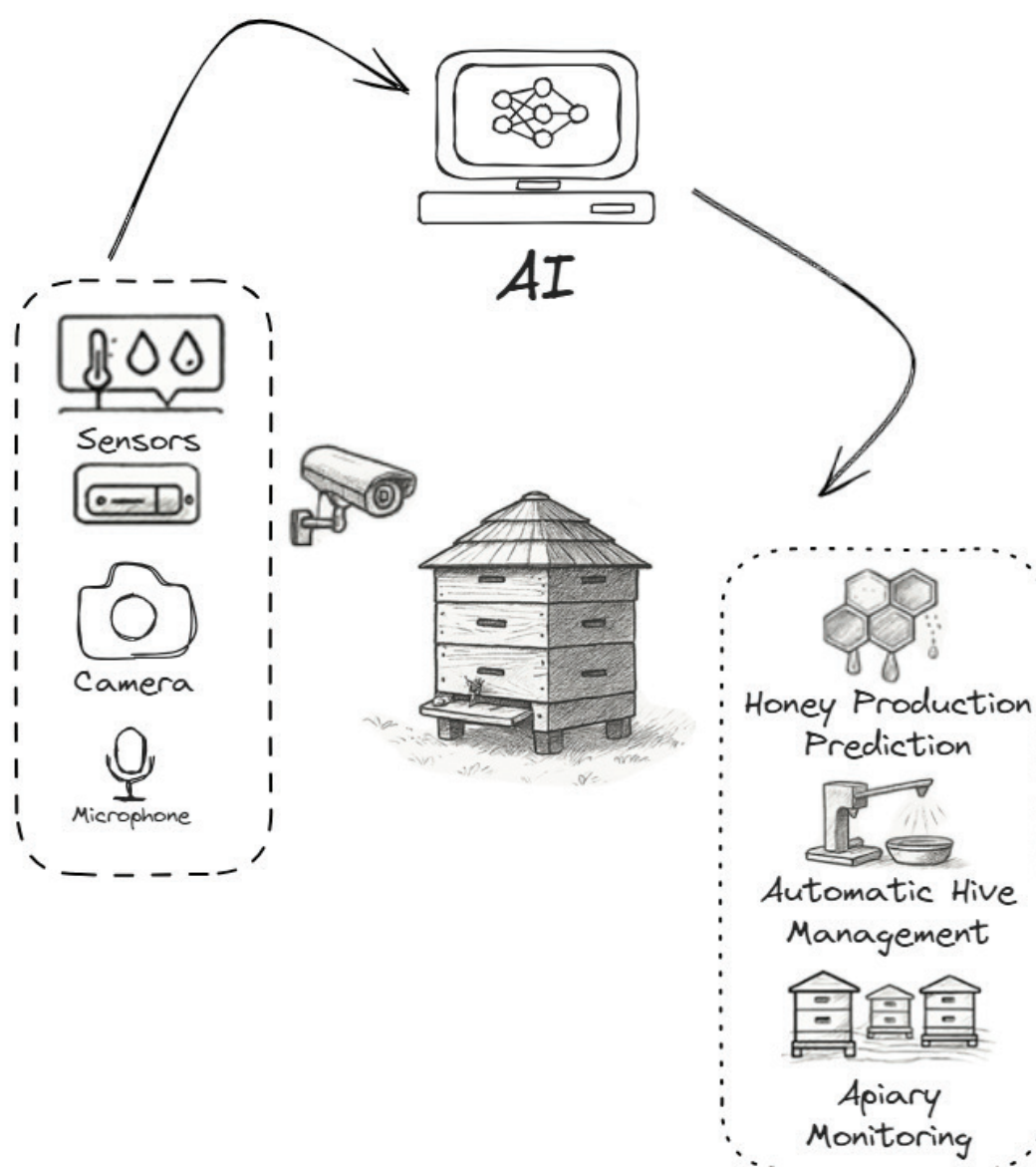


Figure 7. Colony dynamic monitoring for enhancing bee colony productivity.

devices, and self-regulating hive ventilation, leverage AI to respond dynamically to environmental and colony changes. This level of automation not only increases efficiency but also minimises stress on bee populations, ensuring sustainable and productive apiculture practices (see Figure 7).

One of the key applications of AI in the analysis of colony dynamics is monitoring the movements and activity of bees. Thanks to CV and optical sensors, it is possible to track the behaviour of individual bees and their interactions, and analyse changes in activity at different times of day and seasons.

The following technologies are currently used:

- **Vision systems based on deep neural networks (CNNs)** – allow the identification of

individual bees and the classification of their behaviour.

- **Optical and thermal sensors** – record the number of bees entering and leaving, enabling their activity to be assessed, depending on weather conditions.

AI enables the analysis of behavioural patterns, such as periods of intense activity, changes in the number of forager flights, and recognition of the signs of colony stress, e.g., by identifying unusual movement or disturbing flight patterns. The use of AI in colony productivity forecasting is based on the use of ML algorithms to analyse historical data on honey production, bee activity, and environmental conditions. Predictive models allow for the prediction

of hive performance and identification of factors that may affect the efficiency of nectar collection.

The most commonly used approaches include:

- **Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM)** – algorithms used to analyse time series and predict future bee activity based on historical data.
- **Random Forest and XGBoost** – models used for classification and regression that can analyse the impact of weather conditions and colony structure on honey production.
- **Kohonen Self-Organising Maps (SOMs)** – used to group similar patterns in colony activity, allowing for the detection of unexpected changes in hive dynamics.

Such models can help beekeepers predict when a hive will reach its peak production, what interventions can improve collection efficiency, and what factors may pose a threat to the colony. The final element of using AI in analysing colony dynamics is the automation of hive management. Intelligent systems supported by AI algorithms can make decisions in real time by analysing sensor data and suggesting specific interventions.

Modern technologies used in this field include:

- **Rule-Based AI Systems** – automatic algorithms that suggest beekeeper actions based on sensory data.
- **Fuzzy Logic Control (FLC)** – a control method that allows for decision-making in conditions of uncertainty, e.g., determining the best time to expand the hive or start feeding.
- **Deep Reinforcement Learning (DRL)** – a technique used to dynamically adjust conditions in the hive, such as ventilation or food supply.

The integration of these systems with IoT devices allows for the implementation of fully automated hive management, where AI can autonomously analyse the situation in the colony and suggest appropriate interventions without the beekeeper needing to be constantly present.

Environmental Monitoring and Pollination Optimisation

AI-based environmental monitoring systems analyse weather patterns, vegetation availability, and pesticide exposure risks. Satellite imagery and remote sensing techniques help beekeepers determine optimal hive placement for enhanced foraging efficiency. ML models predict flowering cycles and weather conditions, aiding in pollination planning. These insights enable beekeepers to maximise productivity while mitigating risks associated with climate variability and environmental stressors.

The success of beekeeping is intricately linked to environmental factors such as climate conditions, floral resource availability, and landscape suitability for foraging. Changes in weather patterns and habitat degradation can have significant impacts on colony health and pollination efficiency. Traditional methods of environmental assessment, such as manual field observations and historical weather records, are often insufficient for accurately predicting optimal conditions for beekeeping. AI-powered solutions offer a data-driven approach to analysing environmental factors, allowing beekeepers to make informed decisions about hive placement, foraging efficiency, and pollination services. One of the primary AI applications in environmental analysis is weather prediction modelling. ML algorithms process large datasets of meteorological information to forecast temperature fluctuations, rainfall patterns, and seasonal shifts. These predictions help beekeepers anticipate changes in bee activity, schedule hive inspections, and adjust management practices accordingly to mitigate risks associated with extreme weather events. Additionally, remote sensing and satellite imagery provide valuable insights into floral resource distribution. By analysing satellite data and aerial imagery, AI can identify blooming patterns, assess vegetation health, and detect potential foraging hotspots. This information is particularly beneficial for migratory beekeeping operations, where hive placement must be strategically chosen to maximise honey production and pollination efficiency. Another critical aspect of AI-driven environmental analysis is foraging optimisation. ML algorithms can analyse bee movement data, landscape features, and nectar availability to determine the most efficient hive locations. This ensures that colonies have access to diverse and abundant food sources, ultimately enhancing pollination success rates and reducing the risk of nutritional deficiencies. By integrating AI into environmental monitoring, beekeepers can improve their understanding of ecological conditions, enhance pollination strategies, and contribute to the broader efforts of biodiversity conservation. These advancements not only support sustainable beekeeping practices but also help maintain healthy ecosystems essential for global food production.

Modern beekeeping cannot exist in isolation from the surrounding environment, which directly affects the health and efficiency of colonies. Rising global temperatures, changes in the availability of plant resources, and unpredictable weather conditions pose a huge challenge for bees and beekeepers. In this context, AI can play a key role in monitoring the environment and optimising pollination processes. By using advanced data analysis systems, satellite imaging

techniques, and predictive ML models, AI allows the precise determination of optimal conditions for bee health and activity. These systems not only analyse the impact of environmental factors on colonies but also provide information that allows better apiary planning and more effective management of the pollination process. Atmospheric conditions are crucial for bee activity. Too high temperatures, heavy rainfall or strong winds can limit their ability to collect nectar, and unpredictable climate changes are an increasing threat. AI models based on the analysis of weather data help beekeepers predict when colonies will be most active and how changing conditions may affect their work. The most commonly used technologies in this area are:

- **Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM)** – predictive models that allow for the analysis of weather patterns based on historical data and the prediction of periods favourable for collecting nectar.
- **Deep Learning for Weather Forecasting (DLWF)** – deep neural networks used for long-term climate forecasting and the assessment of its impact on bees.
- **AI-based Wind Flow Analysis** – models analysing wind speed and direction, enabling the prediction of periods of low flight activity of bees.

The introduction of these tools allows beekeepers to plan interventions, such as additional feeding or moving hives to more favourable locations, which increases the chances of optimal honey production and more effective pollination.

The availability and diversity of melliferous plants directly affect the productivity of colonies and the quality of pollination. Modern methods of monitoring agricultural and forest areas allow the analysis of available plant resources, enabling the more effective distribution of hives and optimisation of bee performance. The tools and technologies used in this area include:

- **Remote Sensing and Satellite Imaging (GIS + AI)** – analysis of data from satellites and drones to identify areas rich in melliferous plants and assess changes in plant cover.
- **Computer Vision for Plant Identification** – use of image recognition algorithms to determine the species of plants occurring in a given area and assess their health status.
- **Machine Learning for Floral Resource Prediction** – algorithms that learn from previous harvests and predict peak flowering periods in different locations.

AI can help not only track which plants are available to bees in a given season but also predict

changes in the ecosystem and plan activities to support pollination.

Proper placement of hives is crucial for pollination efficiency and colony health. AI can help beekeepers determine ideal locations, taking into account not only plant availability but also microclimate conditions, predator pressure, and the impact of anthropogenic factors. The most commonly used technologies include:

- **Genetic Algorithms for Hive Placement Optimisation** – genetic algorithms that allow for the dynamic optimisation of hive locations based on various environmental variables.
- **Multi-Agent Systems (MAS) in Ecosystem Modelling** – computer simulations that analyse the interactions of bees with the environment and predict the optimal layout of apiaries.
- **AI-Driven Geographic Information Systems (GIS-AI)** – systems that combine geographic data with ML, helping to select places with the greatest pollination potential.

The implementation of such technologies allows beekeepers to not only increase pollination efficiency but also to minimise the risk of colony stress and reduce the negative impact of environmental factors on their health.

Evolutionary Approaches and Optimisation Techniques

The Artificial Bee Colony (ABC) algorithm is a nature-inspired, population-based optimisation technique that mimics the foraging behaviour of honeybee swarms. Originally proposed by Karaboga (Karaboga and Bastruk, 2007), ABC has become a widely studied and applied algorithm in diverse optimisation problems due to its simplicity, flexibility, and effectiveness in exploring complex solution spaces (Karaboga *et al.*, 2012; Beg and Wao, 2019; Aslan, 2020; Dhouib and Miledi, 2022). In the context of intelligent apiculture, ABC holds particular significance as both a metaphorical and practical bridge between natural swarm intelligence and computational problem-solving.

The ABC algorithm models three types of bees – employed bees, onlooker bees, and scout bees – each of which contributes to the collective search for high-quality solutions. Employed bees explore local areas around known food sources (solutions), onlooker bees probabilistically select food sources based on their quality, and scout bees randomly search the environment for new sources. This division of labour allows the algorithm to balance exploitation and exploration, making it suitable for dynamic and multi-objective optimisation tasks (Karaboga and Bastruk, 2007).

Relevance to Precision Beekeeping

While ABC is often used in general-purpose optimisation, its direct relevance to PB lies in its

potential to optimise parameters related to hive management, environmental modelling, and resource allocation. Key applications include:

- **Sensor Placement Optimisation:** Determining optimal locations for environmental sensors within and around hives to ensure accurate data collection with minimal redundancy.
- **Pollination Path Planning:** Simulating and optimising foraging patterns to support efficient crop pollination under controlled pollinator deployment strategies.
- **Resource Management in Smart Apiaries:** ABC can help optimise energy usage in sensor networks, data transmission schedules, or even the distribution of treatment plans in large-scale apiary operations.
- **Disease Spread Modelling:** Leveraging swarm-based search to calibrate models predicting disease propagation based on environmental variables and colony dynamics.

ABC is particularly advantageous for apicultural applications where traditional gradient-based methods are unsuitable due to non-linear, noisy, or multi-modal objective functions. Its biologically inspired nature also makes it well-suited for simulating behaviours within bee colonies themselves, providing additional insights into emergent colony dynamics and resilience.

Despite its strengths, ABC, like other metaheuristic algorithms, faces challenges related to convergence speed, parameter tuning, and scalability to high-dimensional problems. Hybrid approaches – combining ABC with neural networks or reinforcement learning – are currently being explored to address these limitations. Additionally, domain-specific adaptations of ABC for agricultural and ecological systems remain an active area of research, with potential for custom ABC variants tailored to apicultural constraints.

Ethical and Practical Considerations

The integration of AI in PB poses a number of ethical, social and practical challenges that need to be carefully considered to ensure responsible implementation. While AI-based hive monitoring offers numerous benefits, such as improved colony health and optimised beekeeping practices, it also raises serious concerns about data privacy, potential bias in AI models, technology availability, and broader ecological implications. One of the major concerns is data privacy, as AI systems constantly collect and analyse information related to hives, raising questions about data ownership, security and ethical use. Additionally, AI models are prone to bias, which can lead to misleading predictions or incorrect diagnoses, ultimately affecting decision-making processes. Another critical issue is the cost and availability of

AI-based tools, as high-tech solutions may be out of reach for small beekeepers, potentially widening the technology divide in beekeeping. Finally, there are ecological and ethical implications of AI-based interventions, particularly in natural pollination processes, where over-reliance on automation can disrupt the ecological balance.

Data Privacy and Security in AI-Based Hive Monitoring

The use of AI in beekeeping relies on vast amounts of data collected through smart sensors, video surveillance, and cloud-based analytics platforms. These systems continuously record hive activity, environmental conditions, and colony health indicators, providing invaluable information to beekeepers. However, the collection, storage, and use of such data raises serious concerns about privacy, ownership, and data security. One of the main issues is who owns the data collected from AI-based hive monitoring. Should this information belong solely to individual beekeepers, or should technology providers and research institutions have the right to access and analyse it? Many AI-based farming platforms store data on cloud servers, potentially exposing sensitive information to third parties, including corporations, research bodies, and even government agencies. The lack of a clear legal framework governing data ownership in beekeeping increases the risk of unauthorised access and potential misuse. Another challenge is data security and cyber threats. AI-based beekeeping systems are vulnerable to hacking, unauthorised data breaches, and cyberattacks that can compromise not only colony data but also broader agricultural and ecological insights. If AI models are manipulated or data sets are altered, incorrect predictions about hive health and environmental conditions can lead to harmful decisions. To address these issues, strong data protection laws must be established to give beekeepers control over their data while enabling ethical data sharing for scientific research. In addition, encryption techniques and secure data storage solutions must be implemented to minimise the risks associated with cyber threats. Transparency with regard to data usage policies is also essential in building trust between beekeepers and AI developers.

AI Model Bias and Its Impact on Decision-Making

AI models are only as reliable as the data they are trained on. If training data sets are incomplete, unbalanced, or biased, AI-based hive monitoring systems can produce inaccurate predictions, leading to erroneous colony management interventions. This problem is particularly critical in beekeeping, where environmental conditions, bee species, and local beekeeping practices vary widely. One of the main risks of algorithmic bias is incorrect disease

detection. If an AI system is trained primarily on data from a single geographic region or a specific honeybee subspecies, it may fail to recognise diseases or environmental stressors that affect colonies under different conditions. For example, AI trained on European honeybee colonies may have difficulty diagnosing problems in African honeybee populations, leading to incorrect treatment recommendations for hives. Moreover, AI decision-making can be affected by skewed datasets, leading to overreliance on certain parameters while ignoring other key factors. This can result in AI systems incorrectly flagging healthy hives as problematic or failing to detect subtle warning signs that colonies are at risk. If beekeepers blindly trust AI-generated recommendations without verification, biased predictions can result in unnecessary interventions or even colony loss. To mitigate bias in AI-driven beekeeping, it is crucial to develop diverse and representative training datasets, incorporate human oversight into AI decision-making, and implement continuous model refinement to account for regional differences. Additionally, AI developers should ensure transparency in model training and provide beekeepers with insight into how predictions are generated.

Cost and Availability of AI-based Tools for Small Beekeepers

Although AI-based tools have the potential to revolutionise beekeeping, their high cost and technical complexity are barriers to widespread adoption, especially among small and traditional beekeepers. Developing and maintaining AI-based hive monitoring systems often requires significant financial investment, making them more accessible to large commercial enterprises while putting small apiaries at a disadvantage. The cost of AI-based beekeeping tools includes hardware (sensors, cameras, microcontrollers), software (AI algorithms, cloud computing), and maintenance expenses. In addition, many AI solutions require internet connectivity and data storage infrastructure, which may be limited in rural or remote beekeeping locations. As a result, small-scale beekeepers may have difficulty justifying the return on investment when deciding to implement AI in their apiaries. To address this disparity, researchers and developers should focus on creating affordable, open-source AI tools that meet the needs of resource-constrained beekeepers. Government grants, cooperative funding initiatives, and nonprofit organisations can also play a role in subsidising AI adoption in smaller beekeeping operations. The development of user-friendly AI applications that do not require extensive technical knowledge can further facilitate the democratisation of AI in beekeeping.

Conclusion and Future Directions

Beekeeping has played a key role in maintaining the balance of ecosystems and ensuring food security through plant pollination for thousands of years. Today, in the face of growing threats related to climate change, loss of biodiversity, and the increased use of chemicals in agriculture, it is becoming necessary to implement new methods that can support the health of bees and increase the efficiency of breeding. The traditional approach to beekeeping, although effective for centuries, does not always allow for precise monitoring of colonies, the prediction of their needs, or the early detection of threats. It is within this context that modern technologies, and in particular, AI, are playing an increasingly important role in shaping the future of beekeeping. The development of PB is a transition from intuitive methods based on experience to systematic and automated management of apiaries using advanced analytical tools. AI and related technologies, such as image analysis, sound monitoring, environmental sensors, and predictive models, open up new possibilities in diagnosing the health of colonies, predicting their behaviour and optimising the living conditions of bees. Thanks to AI, beekeepers can obtain real-time information on the condition of the hive, identify potential threats (e.g., parasites, diseases, environmental stress), and take appropriate actions before the situation becomes critical. The entire work discusses four key areas of AI use in modern beekeeping in detail:

- **Diagnostics and colony health** – image and video analysis to detect diseases, acoustic monitoring to analyse bee behaviour, intelligent sensors measuring temperature and humidity in hives, and predictive models predicting health problems.
- **Analysis of bee behaviour and production optimisation** – AI systems to track bee activity and movement, forecasting models to assess honey production potential and the automation of apiary management processes.
- **Environmental monitoring and optimisation of pollination** – use of AI-based weather forecasts, analysis of plant resources through satellite data, and intelligent algorithms supporting the layout of hives to maximise pollination efficiency.
- **Ethical and practical challenges** – issues related to data privacy, potential algorithm errors, technology implementation costs, and ecological consequences.

Looking at these areas, it can be seen that modern beekeeping is increasingly resembling an interdisciplinary field, combining biology, ecology, data engineering, and computer science. The

implementation of AI not only supports beekeepers in their daily work but also represents a significant step towards the more sustainable management of pollinator populations, which are the foundation of the global ecosystem. At the same time, the development of these technologies brings with it new challenges, of both a technical and ethical nature. Questions arise regarding how much we can rely on AI in decision-making processes, how to avoid algorithmic biases, and how to ensure that these modern tools are also available to small, traditional apiaries, and not only to large, computerised beekeeping farms.

The integration of AI-driven technologies in colony health monitoring represents a significant advancement in PB. CV and DL techniques enable automated image and video analysis for early disease detection, reducing the need for invasive hive inspections. Acoustic monitoring, powered by AI-based pattern recognition, provides real-time insights into colony behaviour, identifying stress factors such as queen loss or swarming tendencies. Additionally, AI-driven temperature and humidity sensors allow for continuous environmental monitoring, ensuring optimal hive conditions and predicting potential disruptions. ML models further enhance predictive analytics, enabling beekeepers to anticipate health threats before symptoms become visible. Collectively, these AI-powered methods contribute to improved hive management, reduced colony losses, and more sustainable beekeeping practices. However, challenges such as data accuracy, model generalisation, and accessibility for small-scale beekeepers remain.

Despite the significant potential of artificial intelligence and advanced monitoring systems in apiculture, the adoption of such technologies remains uneven across the beekeeping community. One of the key factors influencing this is the demographic profile of beekeepers. In many regions, particularly in Europe and North America, the average age of beekeepers is around 60 years old. This generation has traditionally relied on manual methods – inspections based on sensory experience, handwritten logbooks, and direct intervention in hive management. Many seasoned practitioners have developed a deep, intuitive knowledge of bee behaviour through years of hands-on practice, which can sometimes foster a degree of scepticism toward technological solutions that aim to automate or reinterpret these processes. Additionally, some may perceive digital tools as overly complex, unnecessary, or even intrusive to the natural rhythms of beekeeping.

However, a generational shift is gradually occurring. Younger individuals – often motivated by environmental concerns, a passion for biodiversity, or a desire for self-sufficiency – are increasingly becoming interested in keeping bees. These newer beekeepers tend to be

more open to incorporating modern technologies into their practices, including the use of smartphone apps, digital sensors, remote hive monitoring, and cloud-based data analytics. Their comfort with digital tools and data-driven decision-making presents a promising opportunity to bridge traditional practices with cutting-edge innovations. Moreover, the integration of precision beekeeping tools can serve as an educational aid, helping novice beekeepers make informed choices and shorten the learning curve.

This evolving demographic landscape highlights the importance of developing technologies that are not only scientifically robust but also accessible, user-friendly, and adaptable to a variety of beekeeping contexts. Tools should be designed to complement – not replace – the expertise of experienced beekeepers, while offering new pathways for data-driven management to those just entering the field. Ensuring usability, clear data visualisation, low maintenance, and cost-effectiveness will be key to fostering adoption across generations.

In this context, the research presented in this paper gains additional significance. By systematically categorising and evaluating existing AI methods across various domains – colony health diagnostics, behavioural monitoring, environmental sensing, and predictive modelling – this work offers a foundation for designing practical, scalable systems. Furthermore, the proposed dual-concept power and data architecture (centralised vs autonomous) shows how technological solutions can be tailored to different operational needs and user preferences. Whether in large-scale apiaries or small urban gardens, such flexibility is crucial to encouraging wider adoption.

In conclusion, while technological innovation in apiculture is advancing rapidly, its success depends on more than just algorithmic accuracy or sensor precision. The human dimension – particularly the perceptions, habits, and needs of beekeepers – must be considered in every stage of design and deployment. As the field moves forward, a participatory approach that blends the wisdom of traditional beekeeping with the capabilities of modern AI could foster a new era of sustainable, efficient, and inclusive pollinator management. Empowering both current and future beekeepers through intuitive, supportive technologies will be essential to ensuring the health of honeybee populations – and, by extension, the stability of ecosystems and food systems worldwide.

Statement and Declarations

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used ChatGPT-5 in order to improve the readability

and language of the manuscript. After using this service, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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Abbreviations

Artificial Intelligence (AI)
Artificial Bee Colony (ABC)
Computer Vision (CV)
Deep Learning (DL)
Internet of Things (IoT)
Machine Learning (ML)
Precision Apiculture (PA)
Precision Beekeeping (PB)
Smart Apiculture (SA)

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