Deep Learning and Computer Vision for Honey Bee Health Monitoring: A Systematic Survey and Future Directions

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Abstract
Honey bees are very important for the world's food supply and the health of ecosystems, but their numbers are dropping because of things like Colony Collapse Disorder (CCD), diseases, and environmental stressors. In reaction, AI-powered monitoring systems have come up as a promising way to check on the health of bee hives without bothering them. This paper provides an extensive review of current methodologies in honey bee health monitoring, emphasizing Machine Learning (ML), Deep Learning (DL), Computer Vision (CV), and Internet of Things (IoT)-based techniques. The survey methodically examines cutting-edge techniques across various data modalities, including image, audio, video, and sensor data, and evaluates their efficacy in tasks such as classification, detection, behavioural analysis, and environmental monitoring. A unified taxonomy based on existing frameworks is suggested to group these methods by how they collect and process data, their system architectures, and the fields they are used in. Additionally, a comprehensive dataset and benchmark analysis is performed, emphasizing frequently utilized datasets, evaluation metrics, as well as efficiency trends. The results show that deep learning-based image analysis is very accurate at classifying bee health, and multimodal systems have a lot of potential for making systems more reliable and robust. Nonetheless, obstacles such as restricted dataset availability, computational limitations, absence of standardization, and challenges in real-time implementation endure. To tackle these challenges, the paper delineates essential future research trajectories, encompassing the creation of extensive multimodal datasets, edge AI-driven systems, sophisticated data fusion methodologies, interpretable AI frameworks, as well as predictive analytics for the early identification of diseases. Overall, this survey is a well-organized and thorough reference for researchers and professionals who want to create scalable, intelligent, as well as real-time bee health monitoring systems that help protect biodiversity and support sustainable farming.

Keywords: Honey Bee Health Monitoring, Deep Learning, Computer Vision, Machine Learning, Multimodal Data Fusion, Internet of Things (IoT), Precision Agriculture.

1. Introduction

Honey bees (Apis mellifera) are essential for keeping the world in balance and for growing food. They are the primary pollinators for a lot of wild plants and crops. Pollination is important for more than 75% of the world's food crops, and honey bees are a big part of this process [1], [2]. Their participation not only increases the amount of crops that can be grown, but it also improves the quality and variety of agricultural goods. So, the fact that there are fewer honey bees is a big problem for the health of ecosystems, biodiversity, and the availability of food.

Honey bee colonies have been affected more and more by different biological and stressors from the environment in the last few years. These include parasites (like Varroa destructor), pesticides, climate change, loss of habitat, and diseases. One of the most worrying things that has happened since the number of bees has been going down is Colony Collapse Disorder (CCD). It happens when the worker bees suddenly leave a hive, leaving only the queen and young bees behind [3], [4]. For the past ten years, reports have shown that colony losses have always been too high. The bee loss trends show how important it is to have good monitoring and intervention systems.

Beekeepers had to do a lot of manual checks to make sure their hives are healthy. This takes a lot of time and work, and it's easy to make mistakes. A beekeeper may need to check hundreds of hives daily, which makes it diligently to find diseases or other issues early on [5]. Bee colonies can also get stressed out when there are a lot of people around, which makes illnesses worse. We need to make automated monitoring systems that don't get in the way and can be used on a large scale because of these limits.

Recent advancements in Artificial Intelligence (AI), particularly in Machine Learning (ML), Deep Learning (DL), as well as Computer Vision (CV), have enabled innovative and more intelligent methods for monitoring bee health. Deep learning models, especially Convolutional Neural Networks (CNNs), have been very good at tasks like recognizing patterns, identifying objects, and sorting images. These features let you autonomously find bees, figure off which illnesses they suffer from, and look at how they act using pictures, audio, as well as video data [6] – [8].
Existing research has explored multiple modalities for hive monitoring, including:

- Image-based approaches for detecting bee health conditions and parasites,
- Audio-based techniques for analysing hive activity and anomalies,
- Video analytics for tracking bee movement and behaviour.

Vision-based techniques have gotten a lot of interest because they can give you a lot of visual information about how healthy the bees are and how the hive is doing. Most modern systems, on the other hand, only do one thing, like classify or find things. They don't have a single structure that connects all the different parts into an entirely automated pipeline.

Also, problems like imbalanced datasets, changing weather, limited computing resources, and the requirement for real-time computation make it hard to use such systems in the real world. The attached study demonstrates that standard deep learning models can achieve high accuracy, reaching up to 95% in categorization tasks; however, real-time performance is frequently constrained by computational complexity, particularly in object detection models such as Mask R-CNN.

Figure 1: Evolution of AI-based bee monitoring systems from traditional manual inspection to advanced multimodal and predictive intelligent systems.

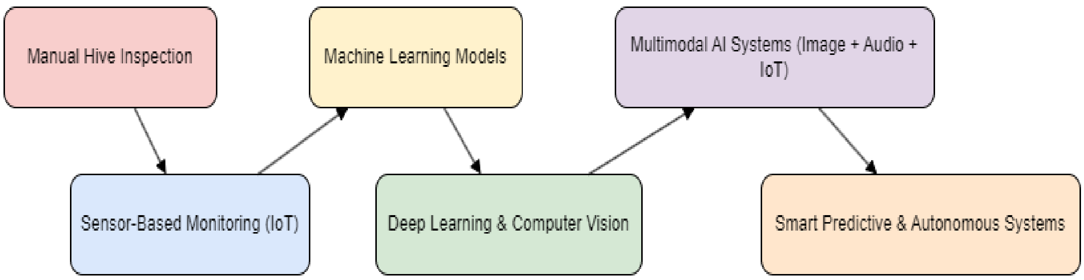


Figure 1 shows how honey bee monitoring systems have changed over time from simple manual methods to more advanced AI-driven intelligent frameworks. This change shows how technology is being used more and more to make hive health assessments more accurate, scalable, and efficient.
Old-fashioned manual inspections have been replaced by smart bee monitoring systems that use AI, machine learning, deep learning, and computer vision. Beekeepers used to mostly check their hives by hand, using their eyes as well as experience to find problems. This method works to some extent, but it takes a lot of job, time, and mistakes, especially when you have a lot of hives to take care of. The next step was to use sensor-based systems for monitoring that used IoT devices to

collect data on things like the weight of the hive, the temperature, and the humidity. These systems could always keep an eye on things, but they couldn't make smart choices because they mostly used threshold-based analysis.

As data analytics improved, machine learning (ML) models were added to gaze at the data that was originally collected and find common patterns that enjoyed to do in the health of the hive. These models helped people find things, but they depended a lot on hand-made includes and structured datasets.

Deep learning (DL) and computer vision (CV) were two big steps forward that made it possible to automatically find features and do very precise tasks like finding bees, classifying diseases, and analyzing behaviour using pictures and videos. A lot of people began using Convolutional Neural Networks, and object detection models during this time.

Recent research has focused on multimodal AI systems that integrate data from various sources, such as images, audio signals, as well as sensor data. This integration makes the framework more reliable and gives us a better idea of how the hive is doing by using data gathered from different places.

The most recent step is all about systems that can think for themselves and drive themselves. AI models not only look at how the hive is doing right now, but they also try to guess what will happen in the future, like disease outbreaks or the collapse of the colony. The goal of these systems is to let people make choices in real time, automate tasks, and connect with precision farming platforms.

The figure demonstrates an obvious trend toward more intelligence, automation, and integration. It stresses the change from reactive monitoring to proactive and predictive AI-driven systems.

Figure 2: General architecture of an AI-based bee health monitoring system illustrating data acquisition, preprocessing, feature extraction, model inference, and decision-making with feedback optimization.

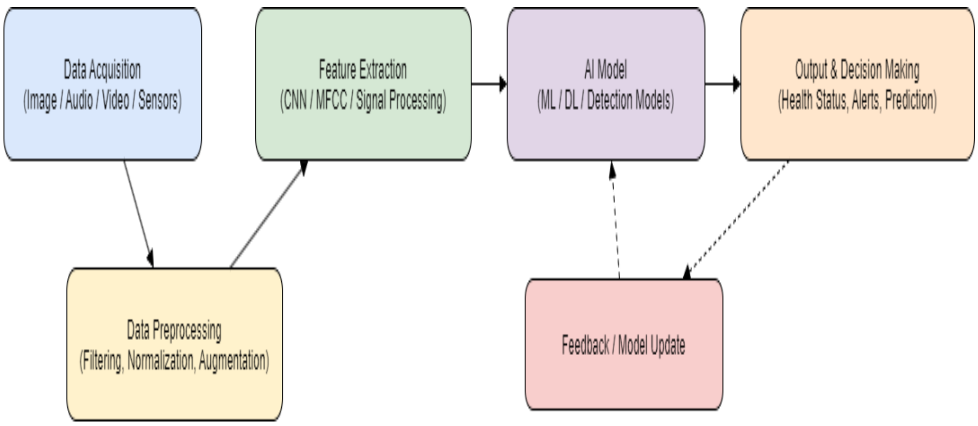
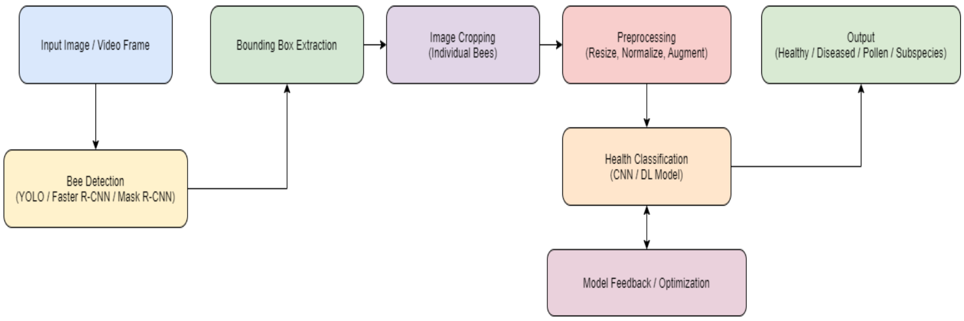


Figure 2 shows the general structure of an AI-based bee health surveillance system, with an emphasis on the whole process from data collection to smart decision-making. This architecture combines different types of data and advanced analytical methods to make hive monitoring automatic and efficient.

The initial phase in the process is the data acquisition layer. It gets data from the hive environment from many places, such as images, audio signals, streams of video, and IoT

sensor data. This data from multiple sources gives us a full picture of bee activity, the state of the natural world, and possible health issues.
The data is then processed during the data preliminary processing phase, which includes things like getting rid of noise, normalizing, resizing, and adding more data. To improve the data and make sure it corresponds for later analysis, these steps must be followed. After preliminary processing, the program does feature standard extraction, which means it looks for useful patterns and traits in the input data. Convolutional Neural Networks (CNNs) are used for image data. For audio signals, people use methods like MFCC (Mel-Frequency Cepstral Coefficients). This step changes raw data into forms that can be used. The AI modelling layer, which has algorithms for deep learning and machine learning like CNNs and Support Vector Machines (SVMs), as well as object detection algorithms like YOLO as well as Mask R-CNN, then gets the features that were found. These models can sort, find, and make educated guesses about how healthy a hive is. The final phase is making decisions and generating output. In this step, the framework gives useful data like the health of the bees, alerts, anomaly detection, and recommendations for how to plan ahead. These outputs may assist beekeepers make quick decisions with all the data they need.
The structure also has a feedback loop that helps the model learn and get better all the time. By adding new data and results to the model, the system becomes more accurate as well as flexible over time.
Overall, this structure shows how it can be used to keep an eye on bee health in a smart and scalable way, with real-time monitoring and the ability to work with smart farming systems.

Figure 3 illustrates the integrated pipeline for automated bee detection and health classification, representing a complete end-to-end workflow commonly used in AI-based hive monitoring systems.



The initial phase in the process is the input stage. It means using cameras and surveillance systems to take videos or images frames of hive environments. These inputs might have a number of bee and a busy background. The next step is to find bees in the input image. This is done using advanced algorithms like YOLO, a faster R-CNN, or Mask R-CNN. This step draws boxes around the bees that were found.
The system then takes out bounding boxes, which show where each bee was found. Then, these coordinates are used to crop the image, which means taking out pictures of each bee from the first frame. This step is very important to make sure that the classification model looks at the right things. The cropped images go through preprocessing, which includes changing their size, normalizing them, and adding more data. These steps make sure that the input information is the same and can be used with deep learning models. The health categorization module then gets the images that have been processed. Convolutional Neural Network (CNNs) or other deep-learning architectures are often

used for this. This module sorts bees into groups based on their health, whether they are sick, carrying pollen, or belong to a certain subspecies.

The output stage puts together the results of the categorization and gives useful data that can be used to keep an eye on the hive, find problems, and make choices. Lastly, a pipeline has a way to get feedback and make itself better. It does this by using new data to keep checking and improving how well the model works. This makes the system better at learning over time and makes it more accurate. This integrated pipeline demonstrates how merging object identification and categorization techniques can yield a fully programmed and scalable system for monitoring bee health.

This survey aims to:

- Provide a systematic overview of AI-based bee health monitoring techniques,
- Compare machine learning, deep learning, and hybrid approaches,
- Analyze datasets, evaluation metrics, and performance trends,
- Identify limitations and open challenges in current systems,
- Suggest future research directions for developing scalable and real-time monitoring solutions.

2. Literature Review

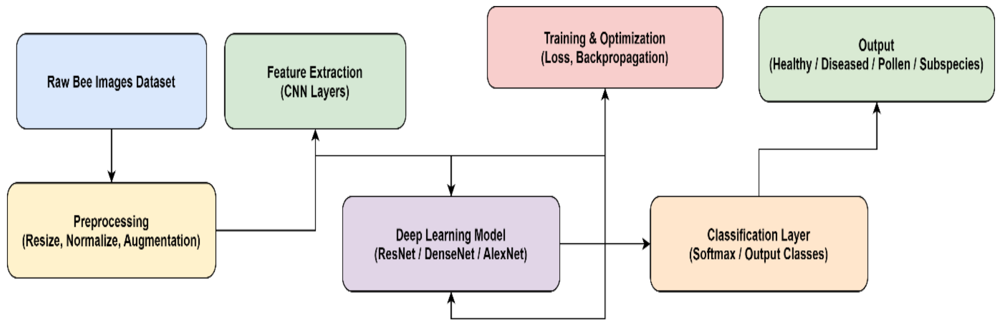
The rapid advancement of AI-based techniques has significantly transformed the domain of accuracy apiculture by enabling the automated monitoring and analysis of honey bee health. There are five main types of literature right now: (i) image-based methods, (ii) audio-based monitoring, (iii) video-driven tracking systems, (iv) smart hive systems that use the Internet of Things (IoT), and (v) hybrid AI frameworks. These methods use computer vision (CV), deep learning (DL), and machine learning (ML) to find diseases, learn how colonies act, and keep an eye on the environment [1]–[4].

2.1 Image-Based Bee Health Monitoring

Image-based approaches represent the most extensively examined domain, attributable to the availability of annotated datasets and the effectiveness of CNN architectures in visual recognition tasks. Pukhov's initial research [5] employed labelled image datasets to develop CNN-based classification algorithms for identifying diseased honey bees. Subsequent research has demonstrated that architectures such as AlexNet, ResNet, and DenseNet significantly enhance classification accuracy by capturing stacked visual features [6], [7].

Braga et al. [1] proposed a two-stage system that integrates object identification and categorization, achieving a precision of up to 95% in categorizing bee health. Similarly, research on parasite detection, particularly Varroa destructor, employed CNN-based image segmentation techniques, achieving detection rates exceeding 90% [8], [9]. Even with these improvements, issues like changes in quality of images, occlusion, and a lack of variety in data sets are still very important.

Figure 4 illustrates the image-based pipeline for honey bee health classification, which is one of the most widely adopted approaches in AI-driven hive monitoring systems. This pipeline focuses on extracting meaningful visual features from bee images to accurately determine their health status.



The process begins with a set of unedited bee pictures that might have various lighting conditions, angles, and backgrounds. In the preprocessing stage, these images are worked on for the first time. This is where you can add more data, resize it, and normalize it. This step improves the data and assists the model work better in general.

The next step is to extract features from the preprocessed images. This is where Convolutional Neural Networks (CNNs) learn on their own about hierarchical features like edges, textures, and complicated patterns which are important to bee health.

After that, the features that were taken out are put into a deep learning model, that is usually based in architectures like ResNet, DenseNet, or AlexNet. The models in question can find complicated links in the data, which lets them put it in the right category.

The classification layer, that is usually done with a Softmax function, then sorts each image into one of several pre-defined groups, like healthy, sick, pollen carriers, or a specific subspecies. The last step tells you what the predicted health status is, which you can use to maintain an eye on things and make decisions. There is also a loop for training and optimizing that uses loss calculations and backpropagation to keep making the model better. This conduit shows how deep learning can be used to classify bee health on a large scale, automatically, and with great accuracy. This is why it is a vital component of smart hive monitoring systems.

2.2 Audio-Based Hive Monitoring

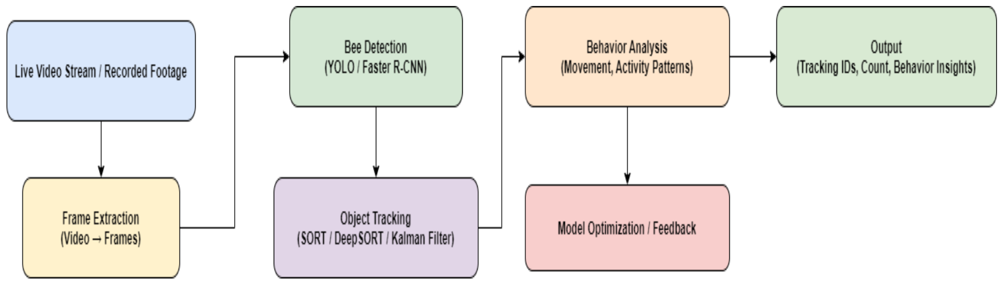
You can now use audio-based monitoring to look at hives without getting to open them up. These systems listen to sounds coming from the hive to figure out how active and in good health the colony is. Kulyukin et al. [10] employed models based on deep learning to categorize hive sounds into classifications such as bee activity, noise, and anomalies, achieving an accuracy exceeding 95%. Nolasco and Benetos [11] also compared CNN as well as SVM models for sorting audio. In cases where there isn't much data, traditional ML models can sometimes work better than DL models.

Other studies used classifiers like Random Forest and KNN and techniques for feature extraction like Mel-Frequency Cepstral Coefficients (MFCCs) [12], [13]. Audio-based systems have advantages because they do not get in the way, though they are easily affected by noise in the environment and require strong preprocessing methods.

2.3 Video-Based and Tracking Systems

Video-based techniques build on image-driven methods by adding information about time, which lets you track movement and behaviour. Florea [14] made a CNN-based structure that automatically detects bees in video streams. It got a F1 score of 0.686. Recent methods use more advanced identifying objects frameworks like YOLO, Faster R-CNN, as well as Mask R-CNN to track things in real time [15], [16]. These systems let you do things like look at foraging patterns, guess how many people there are, and find strange things. Video-based systems, on the other hand, are very resource-intensive and need a lot of processing power, which makes it hard to use them in real-time field settings.

Figure 5 illustrates the workflow of a video-based bee detection and tracking system, which extends image-based approaches by incorporating temporal information for analyzing bee behavior and movement patterns.



The first step in the process is to either stream live video or play back footage that was recorded inside a hive. This going on source of data gives you a lot of time-dependent information that you need to know how bees act.
During the frame extraction step, the video is cut into separate frames so that you can look at it more closely. Detection algorithms take each frame and use it as an image input.
Then, models for object detection like YOLO or a faster R-CNN are used to find and track bees in each frame. This step draws boxes around the bees that were found.
The framework uses object detection methods like SORT, DeepSORT, or Kalman filtering after something is found. Such algorithms give each bee a unique ID while maintaining track of where they go from one shot to the next, which lets you keep an eye on them all the time.
Then, the recorded data is used to study behaviour, that looks at aspects like how people move, how active they are, and how they interact with others. This can help you find things that are not normal, like less activity, strange motion, or signs of illness.

2.4 IoT-Based Smart Hive Monitoring Systems

The integration of IoT with AI has enabled the development of smart hive monitoring systems that collect environmental and biological data in real time. Sensors measuring temperature, humidity, weight, and gas concentration are commonly used to assess hive conditions [17], [18]. These systems often incorporate cloud-based analytics and edge computing for data processing.
Meikle and Holst [19] demonstrated the effectiveness of continuous monitoring systems in improving colony management. IoT-based solutions provide scalability and remote monitoring capabilities; however, they often lack advanced predictive analytics unless integrated with AI models.

Figure 6: IoT-based smart bee hive architecture illustrating sensor data acquisition, edge processing, cloud analytics, and AI-driven decision support.

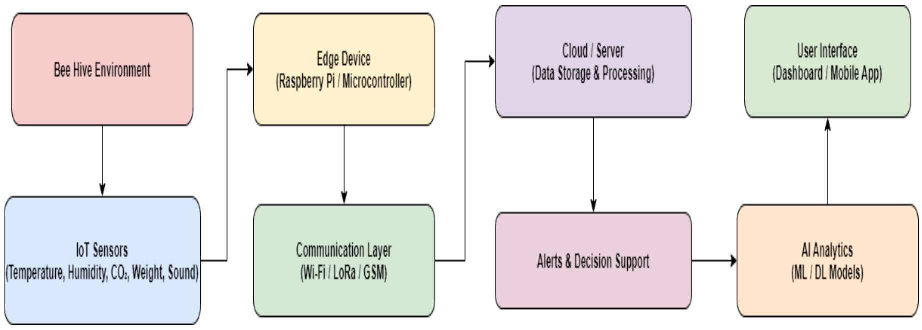


Figure 6 shows the design of an IoT-based smart bee hive surveillance system. This system uses interconnected sensing as well as computing parts to keep an eye on the hive's conditions all the time.

The bee hive the environment is the first part of the system, where different factors that affect the health and activity of the hive are watched. These are environmental and biological factors that have a direct effect on how colonies act and live.

- IoT sensors make up the next layer. They gather real-time information like temperature, humidity, carbon monoxide (CO_2) levels, hive weight, and sound waves. These sensors keep an eye on the hive's conditions all the time and don't bother the bees.
- The data that was gathered is sent to an edge device, like a Raspberry Pi or microcontroller, in which can be processed and filtered for the first time. Edge computing cuts down on latency and the amount of data sent to the cloud.
- The information that has been processed is then sent via the communication layer. This layer can use Wi-Fi, LoRa, or GSM, based on the environment where it is being used and the connectivity needs.
- The cloud or server system stores and processes the data after it has been sent. This is where large-scale managing information and advanced analytics take place. This layer makes it possible to add more storage and processing power.
- The AI analysis module uses algorithms for deep learning and machine learning to look at the data that has been collected, find problems, and guess how healthy the hive will be. This makes it possible to make smart choices based on both current and past data.
- The results are shown through an user interface, like a dashboard or mobile app, so that beekeepers and other interested parties can check on the hives from a distance.
- The system also has an alert as well as decision support mechanism that sends out alerts and suggestions based on identified anomalies or predicted hazards.

2.5 Hybrid AI-Based Monitoring Systems

Recent research trends emphasize hybrid systems that integrate various data formats (image, audio, and sensors data) to enhance robustness and precision. Braga et al. [1] put forward an integrated system that combines object identifying and categorizing showing better performance than models that work alone.

Hybrid frameworks utilize multimodal combining information techniques and ensemble-based learning methods to augment predictive abilities [20], [21]. These systems are especially good at fixing problems that individual methods have, like audio data being too sensitive to noise or images being blocked. But there are still open research problems like data synchronization, complexity of computation, and system integration.

Figure 7: Hybrid multimodal bee monitoring framework integrating image, audio, and sensor data through feature extraction, multimodal fusion, and AI-based prediction.

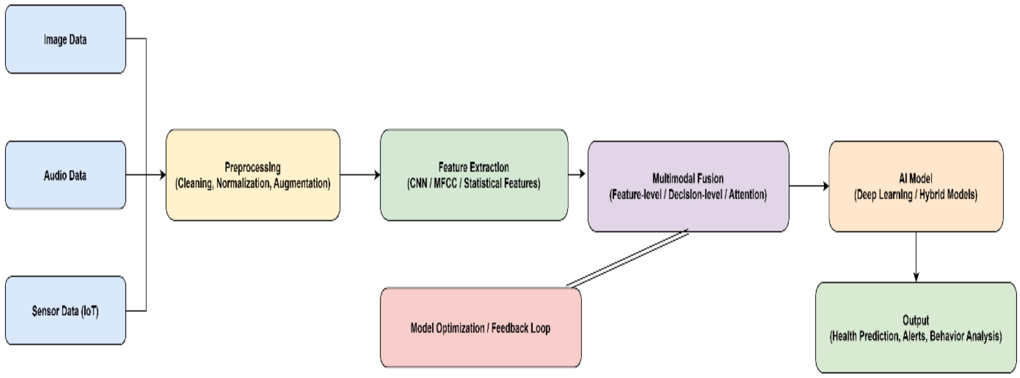


Figure 7 shows a hybrid multimodal structure for keeping an eye on the health of honey bees. This framework combines data from many sources to make predictive models more accurate and reliable. This method solves the problems with single-modality systems by using information from different data types that work well together.

- The framework starts with different types of input, such as image data (from cameras), audio data (from recordings of hive sounds), and sensor data from IoT devices like temperature, humidity, and CO_2 sensors.
- These different types of data sources give a full picture of the conditions in the hive.
- All input data goes through preprocessing, which includes removing noise, normalizing the data, and adding new data to make sure that the quality and consistency of the data are the same across all modalities.
- After preprocessing, the system does feature extraction, which uses techniques that are specific to each modality. For instance, CNNs are used for pictures, MFCCs for sound, and statistical techniques for sensor data. This step changes raw inputs into useful feature representations.
- The multimodal fusion layer then combines the extracted features. This layer brings together information from different modalities. Fusion can happen at different levels, such as feature-level fusion, choice-level fusion.
- The AI modelling layer gets the combined features and uses deep learning or mixed approaches to look at the data and make predictions about hive health, find problems, and do behavioural analysis.
- The output stage gives you useful information like health status forecasts, alerts, or behavioural trends that help you make smart choices.
- The framework also has a feedback as well as optimization loop, which lets model performance get better all the time by using new data and results.

In general, this hybrid multimodal approach is a big step forward in monitoring bee health. It is more accurate, reliable, and flexible than traditional single-modality systems.

2.6 Comparative Analysis of Existing Studies

Below is a structured comparison of key studies in the domain:

Ref	Approach Type	Technique Used	Dataset	Key Objective	Accuracy	Limitations
[1]	Image + DL	CNN + Mask R-CNN	Bee image dataset	Detection + classification	95%	Low FPS

[2]	Image-based	CNN	Kaggle dataset	Health classification	86%	Dataset bias
[3]	Image-based	ResNet	Custom dataset	Disease detection	90%+	Limited data
[4]	Image-based	AlexNet	Bee dataset	Classification	88%	Overfitting
[5]	Image-based	DCNN	Bee images	Health detection	84.9%	Generalization
[6]	Image-based	DenseNet	Custom dataset	Feature extraction	91%	Complexity
[7]	Image-based	CNN	Annotated dataset	Parasite detection	93%	Occlusion
[8]	Image-based	CNN	Synthetic dataset	Varroa detection	93%	Real-world gap
[9]	Image-based	ML + CV	Image dataset	Mite detection	92%	Lighting issues
[10]	Audio-based	CNN	BUZZ1/BUZZ2	Sound classification	96%	Noise sensitivity
[11]	Audio-based	SVM + CNN	Audio dataset	Hive monitoring	94%	Data scarcity
[12]	Audio-based	Random Forest	Audio samples	Classification	91%	Feature dependency
[13]	Audio-based	KNN	Audio dataset	Sound detection	89%	Low scalability
[14]	Video-based	CNN	Video dataset	Bee detection	F1=0.686	Labeling issues
[15]	Video-based	YOLO	Video frames	Real-time detection	85%	Hardware intensive
[16]	Video-based	Faster R-CNN	Custom dataset	Tracking	88%	Latency
[17]	IoT-based	Sensors + ML	Sensor data	Hive monitoring	-	Limited AI
[18]	IoT-based	Cloud + Sensors	Real-time data	Monitoring	-	Network dependency
[19]	IoT-based	Statistical models	Hive data	Continuous monitoring	-	No prediction
[20]	Hybrid	ML + DL	Multimodal	Health prediction	93%	Integration complexity
[21]	Hybrid	Ensemble learning	Mixed data	Disease detection	94%	Computation cost
[22]	Hybrid	Multimodal DL	Combined dataset	Smart monitoring	95%	Scalability

Summary of Literature Review

The literature shows that deep learning-based visual analysis is the most common type of research right now. It gets very accurate results, but it has trouble being used in real time. Audio-based methods let you keep an eye on things without touching them, but they can be affected by noise in the environment. Video-based systems allow for behavioural analysis, but they are expensive to run. IoT-based systems can grow, but they don't have any intelligence unless AI is added. Hybrid approaches are the most promising because they use data from more than one source to make systems more stable and accurate. Nonetheless, challenges including real-time processing, combining data, and scalability persist as unresolved research domains necessitating additional exploration.

3. Dataset & Benchmark Analysis

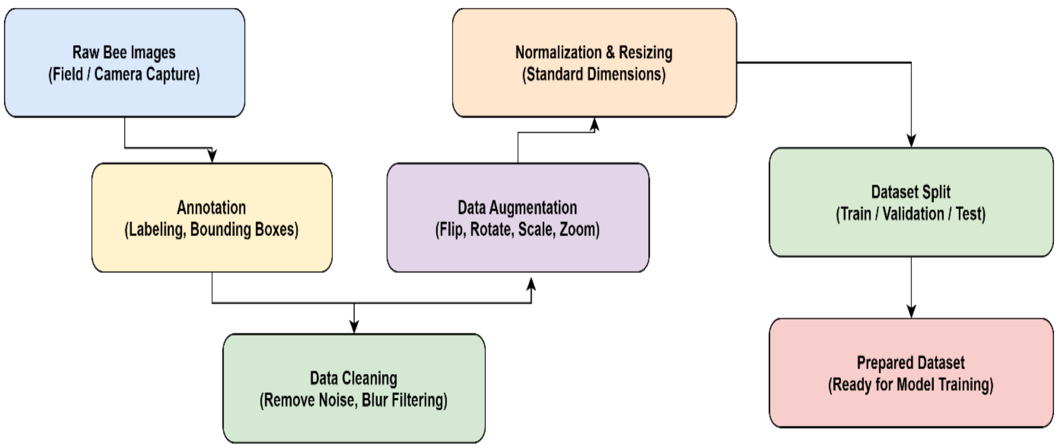
The efficiency and generalization ability of AI-based systems for monitoring the health of honey bees depend a lot on the quality, variety, and labelling of the datasets utilized for training and testing. In this field, datasets come in a variety of forms, such as image datasets, audio datasets, video data sets, and IoT and sensor datasets. Different types of datasets help with different types of analysis, like classification, detection, behaviour analysis, and monitoring the environment. This part gives a full look at commonly used benchmark datasets, what they are like, and how they can be used in AI-based systems for monitoring bee health.

3.1 Image-Based Datasets

Image datasets are the most common tools for figuring out what kind of bee is sick and finding objects. The Honey Bee Annotated Image Dataset, created by Yang [23], is one of the most popular datasets. It has labeled images of bees with information about their health, subspecies, and how they carry pollen. CNN-based classification models have used this dataset a lot because its annotations are well-structured.

Braga et al. [1] used another important dataset that had 5,172 RGB images with different resolutions. These images were later uniformed to 100×100 pixels for training. The dataset contains several health conditions, which makes it possible to classify them into more than one class. Some studies [8] have also created synthetic datasets to add to the training data for tasks like finding parasites, such as identifying Varroa destructor. Even though image datasets work well, they have problems like class imbalance, changes in lighting, occlusion, and a lack of diversity in the real world, which can make models less reliable.

Figure 8: Image dataset annotation and preprocessing workflow illustrating data labeling, cleaning, augmentation, normalization, and dataset preparation for model training.



3.2 Audio-Based Datasets

Audio datasets are very important for monitoring hives without opening them up. The BUZZ1 and BUZZ2 datasets [24] are two of the most popular benchmark datasets. They have labeled audio samples that are sorted into bee sounds, environmental noise, and other insect sounds. A lot of people have used these datasets to classify sounds using both deep learning and traditional machine learning methods.

Kulyukin et al. [10] used these datasets to train CNN-based models and got very high accuracy in classifying them. Another dataset contains annotated hive recordings utilized in sound recognition studies [11], generally consisting of hours of uninterrupted hive audio.

Audio datasets are useful because they let you keep an eye on the hive without bothering it, but they are often affected by background noise, recording quality, as well as environmental interference, which need advanced preprocessing methods.

3.3 Video-Based Datasets

Video datasets give you information about time that is important for tracking and analyzing behavior. Datasets obtained from live streams, exemplified by Explore.org's bee cameras [25], have been utilized to extract frames for object detection and tracking endeavors.

Braga et al. [1] took 2,750 frames from live video streams and then turned them into 251 labeled images for object detection. These datasets make it possible to do things like count bees, track their movement, and look at their activities.

Video datasets, on the other hand, are expensive to process, need frame-level annotation, and often have problems like motion blur, occlusion, and different camera angles.

3.4 IoT and Sensor-Based Datasets

IoT-based datasets are made up of time-series data that sensors inside or around beehives collect. These datasets usually have information like temperature, humidity, hive weight, CO_2 levels, and sound signals [17], [19]. These kinds of datasets are employed for finding unusual patterns, keeping an eye on the environment, and making predictions. Meikle and Holst [19] show how sensor data may be employed to track changes in colony health over time by using continuous monitoring datasets. The main benefit of IoT datasets is that they can give you real-time, continuous streams of data. However, they don't give you direct visual or biological knowledge unless you combine them with image or audio data.

3.5 Multimodal and Hybrid Datasets

Recent studies stress the need for multimodal datasets that include image, audio, as well as sensor data to make predictions more accurate and reliable. These datasets are still being developed and are often made for specific studies [20], [22].

Multimodal datasets make it possible to combine data from different sources, which lets models use data gathered from different sources that works well together. However, there are problems with data synchronization, different data formats, and more complicated calculations.

3.6 Comparative Dataset Summary

The following table summarizes key datasets used in honey bee health monitoring research:

Ref	Dataset Name	Type	Size	Data Modality	Annotations	Application	Key Features	Limitations
[23]	Honey Bee Anno	Public	~5,000+	Image	Health, subspecies, pollen	Classification	Well-labeled,	Class imbalance

	tated Images (Yang)		images			multi-class	
[1]	Braga Dataset	Custom	5,172 images	Image	Health labels	Classification	High accuracy benchmark	Limited diversity
[8]	Synthetic Varroa Dataset	Synthetic	~5,000 images	Image	Parasite labels	Detection	Augmented data	Not real-world
[24]	BUZZ1	Public	4,000+ samples	Audio	Sound classes	Audio classification	Clean labeled audio	Noise sensitivity
[24]	BUZZ2	Public	4,000+ samples	Audio	Sound classes	Hive monitoring	Balanced dataset	Limited environment
[11]	Hive Audio Dataset	Custom	12+ hours	Audio	Activity labels	Sound analysis	Continuous data	Annotation effort
[25]	Explore Bee Videos	Public	2,750 frames	Video	Bounding boxes	Detection	Real-world data	Motion blur
[1]	Annotated Detection Dataset	Custom	251 images	Image	Bounding boxes	Object detection	High-quality labels	Small size
[17]	IoT Hive Dataset	Custom	Time-series	Sensor	Environmental	Monitoring	Real-time data	No visual info
[19]	Continuous Hive Moni	Custom	Long-term data	Sensor	Trends	Prediction	Longitudinal data	Limited ML use

	toring							
[20]	Multimodal Dataset	Custom	Mixed	Image + Audio + Sensor	Combined labels	Hybrid models	High accuracy	Complex integration
[22]	Smart Hive Dataset	Custom	Mixed	Multimodal	Multi-label	AI systems	Robust prediction	Scalability

3.7 Benchmarking Metrics and Evaluation Standards

Across these datasets, several evaluation metrics are commonly used:

- Accuracy – Overall correctness of classification
- Precision & Recall – Class-wise performance
- F1-Score – Balance between precision and recall
- Intersection over Union (IoU) – Used in object detection
- FPS (Frames Per Second) – Real-time performance indicator
- ROC-AUC – Model discrimination capability

The attached study shows that classification models can be up to 95% accurate, while models for object detection can be up to 82% accurate when using IoU-based evaluation. But because of how hard it is to compute, real-time performance is still a problem.

Summary of Dataset Analysis

The analysis reveals that:

- Image datasets dominate research due to ease of annotation and compatibility with deep learning models.
- Audio datasets provide non-invasive monitoring, but require noise handling.
- Video datasets enable behavioural insights, but are computationally expensive.
- IoT datasets offer continuous monitoring, but lack direct biological interpretation.
- Multimodal datasets are the future, offering improved robustness but requiring complex integration.

A major research gap lies in the availability of large-scale, standardized, multimodal benchmark datasets, which are essential for developing scalable and real-time AI-based bee monitoring systems.

4. Unified Taxonomy of AI-Based Bee Health Monitoring Systems

This section provides a unified taxonomy based on existing frameworks to methodically arrange the various methodologies addressed in the literature. The taxonomy combines different aspects, such as data modality, analytic approach, the system's structure and application objectives. This gives researchers a structured way to look at current research and figure out where it should go next.

This taxonomy provides a multi-dimensional perspective, allowing researchers to comprehend the interactions of various techniques within a comprehensive monitoring pipeline, in contrast to the isolated classifications found in previous studies.

4.1 Taxonomy Overview

The proposed taxonomy is structured into four primary layers:

1. ***Data Acquisition Layer*** – Type of data collected (image, audio, video, sensor)

2. ***Processing Layer*** – Preprocessing and feature extraction techniques
3. ***Modeling Layer*** – Machine learning and deep learning algorithms
4. ***Application Layer*** – Final use cases such as detection, classification, and prediction

Figure 9: Unified taxonomy of AI-based bee health monitoring systems, categorizing approaches based on data acquisition, processing techniques, modeling methods, and application domains.

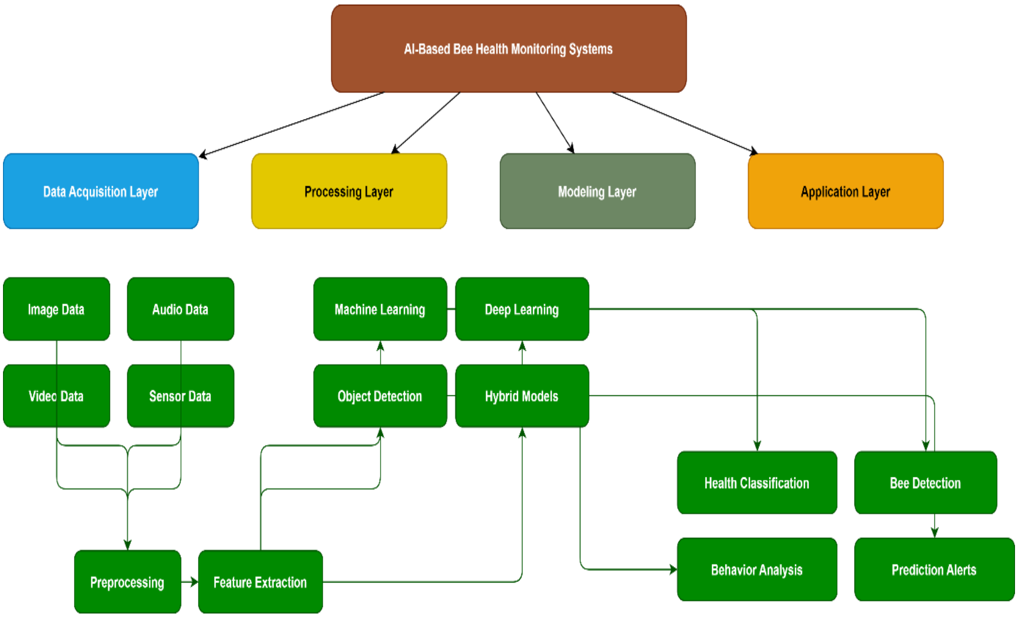


Figure 11 shows an integrated taxonomy of AI-based honeybee health monitoring systems. It organizes the different approaches into four main categories: gathering, processing, modeling, and application. This taxonomy is a complete way to sort and look at the different methods that have been talked about in the literature. At the highest level, the taxonomy shows that AI-based bee health monitoring systems are an integrated field that brings together different technologies and data sources. The first layer, data acquisition, sorts systems based on the types of input they can take, such as video, audio, images, and sensor data. Each type of data gives us different information about the hive. For example, image and video data helps us see what's going on, audio data records hive activity, and sensor data gives us measurements of the environment.

Processing, which is the second layer, includes preprocessing and the extraction of features methods. Normalization, filtering, and augmentation are all parts of preprocessing that make sure the data is good. Feature extraction, on the other hand, turns raw data into useful representations that machine learning models can use. The third layer, modeling, includes a wide range of analytical methods, such as traditional machine learning techniques, deep learning architectures like CNNs and RNNs, models for object detection like YOLO and R-CNN, and hybrid models that use more than one technique. This layer shows how AI methods have changed over time to become more complex and accurate.

The last layer, application, shows how these systems can be used in real life, such as for health classification, bees detection, behavior analysis, and predictive analysis. These programs directly help with monitoring hives, finding diseases, and making decisions. In general, this taxonomy shows that AI-based bee monitoring systems are multi-dimensional and points out the trend towards multimodal, intelligent, and incorporated solutions. It also lays the groundwork for finding gaps in research and pointing the way for future progress in the field.

4.2 Data Modality-Based Classification

The first dimension of the taxonomy categorizes systems based on the type of data modality used. Existing literature primarily focuses on four categories:

- Image-Based Systems – Used for disease detection, classification, and parasite identification [1], [5]
- Audio-Based Systems – Used for hive activity monitoring and anomaly detection [10], [11]
- Video-Based Systems – Used for tracking and behavioral analysis [14], [15]
- Sensor-Based Systems (IoT) – Used for environmental monitoring [17], [19]

Every modality has its own pros and cons. For example, image-based systems are very accurate but need labelled datasets, while audio-based systems are good for non-invasive monitoring but are sensitive to noise.

4.3 Technique-Based Classification

The second dimension classifies approaches based on analytical techniques and algorithms used:

- Traditional Machine Learning (ML):
  Includes SVM, Random Forest, KNN, Logistic Regression [12], [13]
- Deep Learning (DL):
  Includes CNN, RNN, LSTM, ResNet, DenseNet [6], [7]
- Object Detection Models:
  Includes YOLO, Faster R-CNN, Mask R-CNN [15], [16]
- Hybrid Models:
  Combines ML and DL or multimodal data fusion [20], [22]

Deep learning dominates recent research due to its superior feature extraction capabilities, especially in image and video-based applications.

4.4 System Architecture-Based Classification

From a system perspective, existing works can be categorized into three architectural types:

1. Standalone Systems:
   Perform a single task such as classification or detection
2. Pipeline-Based Systems:
   Combine multiple stages such as detection → classification (as seen in Braga et al. [1])
3. End-to-End Intelligent Systems:
   Fully automated systems integrating data acquisition, processing, and decision-making

Pipeline-based systems are currently the most widely adopted, while end-to-end systems represent the future direction for real-time deployment.

Figure 10: Classification of AI-based bee monitoring system architectures into standalone, pipeline-based, and end-to-end intelligent systems, highlighting their structural differences and levels of automation.

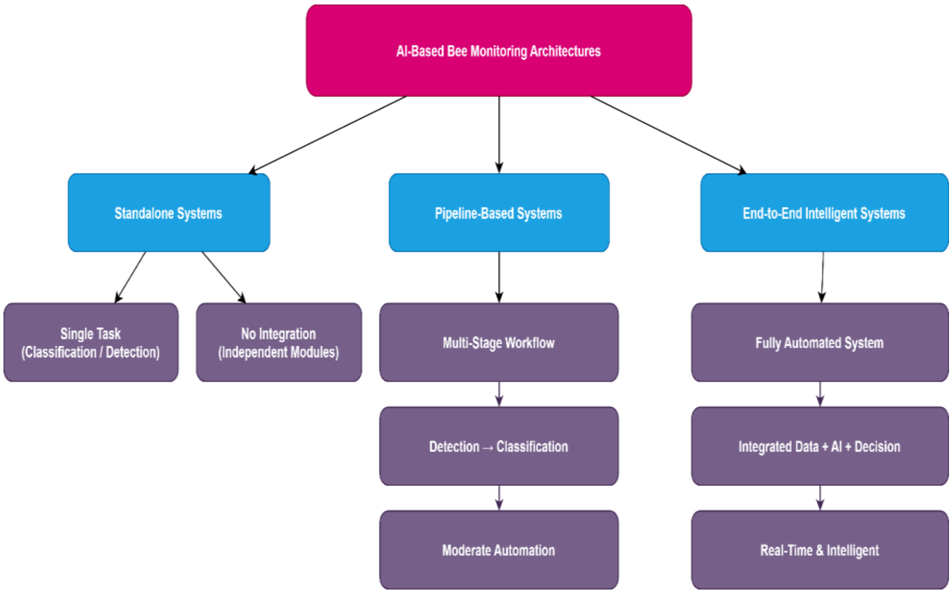


Figure 13 shows how AI-based bee monitoring systems can be grouped based on their architecture. There are three main types: standalone systems, pipeline-based systems, as well as end-to-end intelligent systems.

Standalone systems are the simplest type of architecture. They do one task, like classification or detection, without working with other parts. These systems are simple to set up, but they can't grow or be automated.

Pipeline-based systems create a multi-stage workflow by linking different parts, like detection and classification, in a specific order. By combining several processing steps, this architecture makes it possible to automate some tasks and improve performance. End-to-end intelligent systems are the most advanced type of architecture. They combine data collection, processing, modelling, and decision-making into one system. These systems can be used in smart agriculture settings because they support continuous surveillance and smart predictions.

This classification shows how system architectures have changed from simple models that only do one job to fully integrated and intelligent devices, which shows how automation and complexity have grown.

4.5 Application-Based Classification

The final dimension categorizes systems based on their application objectives:

- Health Classification – Identifying diseases and abnormalities
- Object Detection – Detecting bees and parasites
- Behaviour Analysis – Tracking movement and activity
- Environmental Monitoring – Analysing hive conditions
- Predictive Analytics – Forecasting colony health trends

Most current systems focus on classification and detection, while predictive analytics remains relatively underexplored.

4.6 Unified Taxonomy Summary Table

Ref	Data Type	Technique	Architecture	Application	Key Contribution
[1]	Image + Video	CNN + Mask R-CNN	Pipeline	Detection + Classification	Integrated system
[5]	Image	CNN	Standalone	Classification	Baseline model

[6]	Image	ResNet	Standalone	Disease detection	Deep feature extraction
[10]	Audio	CNN	Standalone	Sound classification	High accuracy
[11]	Audio	SVM	Standalone	Hive monitoring	ML comparison
[14]	Video	CNN	Standalone	Detection	Early video approach
[15]	Video	YOLO	Pipeline	Tracking	Real-time detection
[16]	Video	Faster R-CNN	Pipeline	Detection	Improved accuracy
[17]	Sensor	ML	Standalone	Monitoring	IoT integration
[19]	Sensor	Statistical	Standalone	Prediction	Continuous monitoring
[20]	Multimodal	Hybrid ML/DL	Pipeline	Prediction	Data fusion
[22]	Multimodal	DL	End-to-End	Smart monitoring	Advanced system

4.7 Insights and Research Directions
The unified taxonomy highlights several key insights:
- Deep learning-based image analysis dominates current research due to high accuracy.
- Multimodal systems are emerging as the most promising approach, combining strengths of different data types.
- Pipeline architectures are widely adopted, but lack full automation.
- Real-time deployment remains a major challenge, especially for object detection models.
- Predictive and intelligent decision-making systems are underexplored, presenting opportunities for future research.

Conclusion of Taxonomy Section
This taxonomy offers a coherent and organized view of AI-based bee health surveillance systems, bringing together research that is currently scattered. It not only helps people understand better by arranging existing approaches across many dimensions, but it also finds important research gaps, especially in real-time processing, multimodal integration, and scalable deployment.

5. Proposed Future Directions and Open Issues
Even though AI-based systems for monitoring the health of honey bees have come a long way, there are still some important problems and open research questions that need to be solved. While current methods show great accuracy in controlled settings, they still have problems with scalability, robustness, and being able to be used in real-time in the real world. This section describes the most important areas for future research that came out of the analysis of the unified taxonomy and dataset.

5.1 Development of Large-Scale Multimodal Benchmark Datasets
One of the biggest problems with current research is that there aren't any standardized, large-scale, or multimodal datasets. Most studies depend on small, domain-specific data sets (e.g., image-only or audio-only), which limits how well models can be used in other

situations.
Future research ought to concentrate on:
- Making multimodal datasets that include images, audio, video, as well as sensor data available to the public
- Making sure that the environment is different (lighting, seasons, types of hives)
- Adding detailed notes about things like disease stages and behaviour patterns These kinds of datasets will make it possible to create strong and transferable AI models, which will get around the problems with current single-modality datasets.

5.2 Real-Time and Edge AI-Based Monitoring Systems
Deep learning models are very accurate, but they can't be used in real-time settings because they are too hard to compute and the hardware isn't powerful enough. For example, Mask R-CNN and other object detection models have low FPS, which makes them hard to use in real time.
Future directions include:
- Development of lightweight models (e.g., MobileNet, Tiny-YOLO)
- Implementation of edge AI solutions using embedded systems (e.g., Raspberry Pi, NVIDIA Jetson)
- Optimization techniques such as model pruning, quantization, and knowledge distillation

These methods will make it possible to set up monitoring systems in the field that are low-latency, energy-efficient, and scalable.

5.3 Robust Multimodal Data Fusion Techniques
While multimodal systems show promise, effective data fusion strategies remain an open challenge. Current approaches often use simple fusion techniques that fail to fully exploit complementary information across modalities.
Future research should explore:
- Attention-based fusion models for adaptive weighting of modalities
- Graph Neural Networks (GNNs) for relational data modelling
- Transformer-based architectures for cross-modal learning

These techniques can significantly enhance prediction accuracy and robustness, particularly in noisy or incomplete data scenarios.

5.4 Predictive Analytics and Early Disease Detection
Most existing systems focus on reactive analysis (detecting current conditions) rather than predictive modelling. Early prediction of diseases such as Colony Collapse Disorder (CCD) remains largely unexplored.
Future research directions include:
- Time-series modelling using LSTM and Temporal CNNs
- Integration of historical hive data for trend analysis
- Development of early warning systems for disease outbreaks

Predictive analytics can significantly improve preventive intervention strategies, reducing colony losses.

5.6 Standardization of Evaluation Metrics and Benchmarking
Another critical issue is the lack of standardized evaluation protocols across studies. Different datasets and metrics make it difficult to compare models objectively.
Future work should focus on:
- Establishing benchmark datasets and evaluation protocols
- Defining standard metrics for classification, detection, and real-time performance

- Creating open benchmarking platforms for reproducible research

Standardization will enable fair comparison and accelerated progress in the field.

5.7 Integration with Smart Agriculture and Precision Farming

AI-based bee monitoring systems should be integrated into broader smart agriculture ecosystems. Bees are critical indicators of environmental health, and their monitoring can provide insights into crop conditions.

Future opportunities include:

- Integration with precision agriculture platforms
- Linking bee activity data with crop yield prediction models
- Development of decision support systems for farmers and policymakers

Such integration will enhance the economic and ecological impact of bee monitoring technologies.

5.8 Scalability, Deployment, and Real-World Challenges

Finally, practical deployment introduces challenges such as:

- Hardware limitations in rural environments
- Network connectivity issues
- Maintenance and cost constraints

Future research should focus on:

- Designing cost-effective and scalable solutions
- Developing offline-capable AI systems
- Ensuring robust performance under diverse real-world conditions

5.9 Summary of Open Issues and Future Directions

Issue	Current Limitation	Future Direction
Dataset Availability	Small, unimodal datasets	Large-scale multimodal datasets
Real-Time Processing	Low FPS, high computation	Edge AI, lightweight models
Data Fusion	Simple fusion techniques	Attention-based multimodal fusion
Explainability	Black-box models	XAI integration
Prediction	Reactive systems	Predictive analytics
Benchmarking	No standard metrics	Unified evaluation frameworks
Integration	Isolated systems	Smart agriculture integration
Deployment	Limited scalability	Cost-effective, robust systems

Conclusion of Future Directions

The future of AI-based monitoring of honey bee health depends on creating smart, scalable, and multimodal networks that can work in real time and make predictions. Fixing the problems that have been found will not only make technology work better, but it will also help sustainable farming, protect biodiversity, and make sure that everyone has enough food.

6. Conclusion

This survey provided a thorough examination of AI-driven honey bee health monitoring systems, underscoring the increasing significance of intelligent technologies in tackling issues associated with pollinator decline, the environment sustainability, and worldwide food security. The study systematically analyzed existing literature, datasets, and methodologies to elucidate the utilization of Machine Learning (ML), Deep Learning (DL), Computer Vision (CV), along with IoT-based systems in monitoring and evaluating hive health.

The paper presented a cohesive taxonomy formulated from existing frameworks, classifying contemporary methodologies according to data modality, analytical methods, system design, and app domains. This taxonomy helped bring together different research efforts and gave a complete picture of how to design and build intelligent bee monitoring systems. The dataset as well as benchmark analysis also showed that image-based datasets are still the most common in research, but there is a growing trend toward integrating multiple types of data, which could make models much more robust and accurate.

The literature review shows that deep learning methods, especially CNNs as well as object detection models, work very well for tasks like finding bees and classifying their health. The analysis, however, also pointed out some problems, such as limitations in the dataset, the difficulty of the calculations, the lack of standardization, as well as the problems with deploying the system in real time. Additionally, the majority of current systems are reactive, concentrating on the analysis of the present state rather than on predictive modelling.

To solve these problems, this survey found important future directions, such as the creation of large multimodal datasets, real-time systems based on edge AI, advanced data fusion methods, explicable AI models, and forecasting frameworks. Combining these innovations with smart farming ecosystems could lead to scalable and smart monitoring solutions.

In conclusion, although AI-driven bee health monitoring has advanced considerably, there is still considerable potential for further innovation. Future research should concentrate on creating resilient, comprehensible, and instantaneous systems capable of functioning efficiently in practical settings. These kinds of improvements will not only make beekeeping more efficient, but they will also help with the bigger goals of protecting the environment, preserving biodiversity, and making sure that everyone has enough food.

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