Unsupervised Acoustic Detection of Queenless Hives in Honeybees (*Apis mellifera ligustica*)

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Abstract. *The absence of a queen bee directly compromises the survival of the colony. Accurately detecting this condition is essential for modern beekeeping, but traditional methods rely on invasive manual inspections. In this paper, we propose an automated and non-invasive approach based on unsupervised machine learning to identify queenless hives through bee sound analysis. Mel spectrograms extracted from real audio recordings of Apis mellifera ligustica were processed using a convolutional autoencoder. The resulting latent representations were clustered using HDBSCAN, and labels were applied only in the final validation step. The model achieved 98.78% accuracy, outperforming supervised approaches reported in the literature. To the best of our knowledge, no previous study has investigated the acoustic detection of queenless honeybee hives using unsupervised learning. Our results show the potential of unsupervised bioacoustic analysis and support advances in precision beekeeping within data-centric e-Science.*

1. Introduction

Honeybees play a crucial role in pollination, ecosystem sustainability, and global food security, contributing to nearly 75% of pollinator-dependent crops [FAO 2018, Klein et al. 2007]. However, factors such as habitat loss and climate change have led to a global decline of approximately 40% of bee species [Brown et al. 2016, Sánchez-Bayo and Wyckhuys 2019], highlighting the urgent need for effective monitoring methods [Potts et al. 2010].

Traditionally, beekeepers rely on manual hive inspections to evaluate colony health, particularly to verify the presence of a healthy queen. Although effective, these inspections are time-consuming, labor-intensive, and can disturb and stress the bees. As an alternative, precision beekeeping techniques have explored remote and non-invasive hive monitoring solutions [Zacepins et al. 2015, Braga et al. 2020, Rafael Braga et al. 2020].

The presence of a queen bee is among the most critical factors to monitor, since her absence may trigger colony instability and lead to its collapse [Robles-Guerrero et al. 2017]. In this context, acoustic signals produced by bees have proven useful for inferring colony conditions [Quaderi et al. 2022]. Some works suggest that queen presence or absence correlates with specific sound patterns, such as piping by virgin queens [Michelsen et al. 1986], or low continuous tones typical of queenless hives [Woods 1956]. Based on this, several studies have used acoustic features—e.g., spectrograms and Mel-Frequency Cepstral Coefficients (MFCCs)—combined with machine learning algorithms, such as Support Vector Machines (SVMs), Multilayer Perceptrons (MLPs), and Convolutional Neural Networks (CNNs), to classify hive states [Otesbelgue et al. 2025, Uthoff et al. 2023].

Although some supervised models yield good results, they require labeled data, typically obtained via manual inspection. Moreover, these models must be retrained for each new bee colony, as no universal model exists for different species or habitats. Conversely, unsupervised approaches remain underexplored but offer advantages by identifying patterns based solely on the data structure, without depending on prior labeling.

In this paper, we explore the use of unsupervised learning to detect the presence of a queen bee in hives based on audio signals. Specifically, we assess the HDBSCAN algorithm, which can group patterns of varying densities, offering greater noise tolerance and reduced sensitivity to hyperparameter settings. Our goal is to contribute to a more robust, adaptable, and scalable approach for automated hive monitoring, expanding the use of precision beekeeping in real-world scenarios.

2. Methodology

The object of our study was real audio recordings capturing the activity of honeybee colonies (*Apis mellifera ligustica*) (Figure 1). The dataset consists of audio recordings from two beehives, each recorded in two distinct conditions: (i) queenless, where the queen bee is absent, and (ii) normal, where the hive appears healthy and undisturbed [Nolasco et al. 2019a]. For each condition, one full day of recordings was collected per hive. Each audio file is approximately 10 minutes long. In total, the dataset includes 576 recordings, evenly split between the two classes (queenless and normal), representing two hives over two days in each condition.

(a) (b)

Figure 1. Honeybees from the audio dataset (a) hive frame during inspection; (b) close-up of worker bees. Source: Profa. Stefania Cecchi [s.cecchi@staff.univpm.it].

The methodological design comprises 4 sequential steps (Figure 2): preprocessing of the acoustic data (subsection 2.1), training of a deep learning model for feature extraction (subsection 2.2), clustering of the extracted features (subsection 2.3), and statistical validation of the results (subsection 2.4).

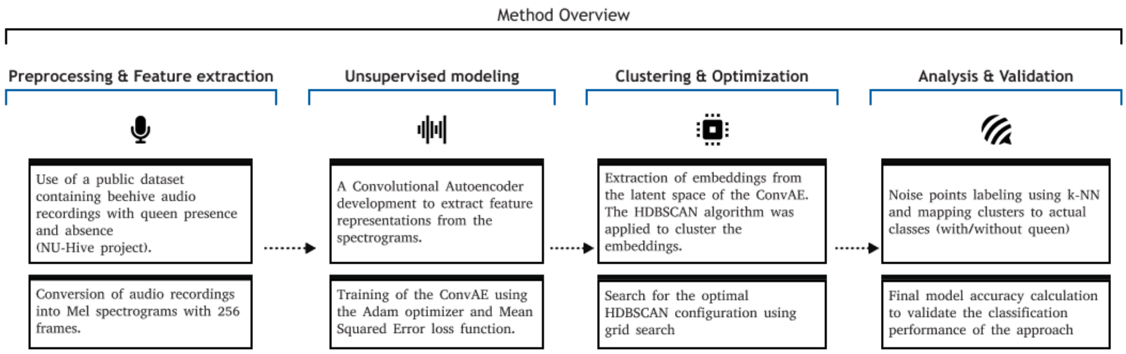

Figure 2. Method design overview.

2.1. Preprocessing and Feature Extraction

The initial pre-processing stage consisted of converting the audio files into Mel spectrograms. This process used a sampling rate of 22,050 Hz, 128 Mel bands, and a fixed length of 256 time frames. To ensure the dimensional uniformity of the model inputs, the *zero-padding* technique was applied to spectrograms shorter than the defined length, while those exceeding this limit were truncated. Feature extraction was conducted based on the latent representations learned by a convolutional *autoencoder* (ConvAE). The training of this model was performed over 10 epochs, using the Adam optimizer with a learning rate of 1×10^{-3} and the mean squared error (MSE) as the loss function. Subsequently, the dimensionality of the latent representations extracted by the *encoder* portion of the ConvAE was reduced using the t-SNE (*t-distributed Stochastic Neighbor Embedding*) algorithm, aiming to facilitate the visualization and subsequent analysis of the clusters.

2.2. Unsupervised Modeling

An unsupervised learning approach was adopted for the data analysis. The main advantage of this approach over supervised learning lies in its ability to learn intrinsic and robust feature representations (*features*) directly from the raw data (spectrograms), without the need for labels during the main model's training phase. This allows the model to autonomously discover patterns and structures in the acoustic data, a particularly valuable characteristic in scenarios where data labeling is a costly, time-consuming, or error-prone process. The pre-existing labels in the dataset were used exclusively in the final validation stage to assess the effectiveness of the generated clusters in the classification task, and not to train the feature extraction model.

2.3. Clustering and Optimization

The low-dimensional latent representations, obtained in the previous step, were processed by the HDBSCAN (*Hierarchical Density-Based Spatial Clustering of Applications with Noise*) clustering algorithm. To refine the quality of the clusters, a hyperparameter optimization process was performed, specifically for *min_cluster_size*, *min_samples*, and *cluster_selection_epsilon*. The objective of this optimization was to maximize the clustering quality metrics, which for this study were the Silhouette [Rousseeuw 1987], Calinski-Harabasz [Calinski and Harabasz 1974], and Davies-Bouldin [Davies and Bouldin 1979] indices.

2.4. Analysis and Validation

The final validation of the results was conducted to assess the model's performance on the binary classification task (presence or absence of the queen). For the data points that HDBSCAN classified as noise, the k-nearest neighbors (k-NN) algorithm was applied for the imputation of a cluster label, ensuring that all samples were included in the evaluation. The model's performance was quantified by the accuracy metric. Additionally, the classification quality was inspected through the analysis of the confusion matrix, which details the distribution of correct and incorrect classifications between the classes.

3. Results and Discussion

Figure 3 illustrates the two-dimensional projection of the embeddings generated by the model, after dimensionality reduction with t-SNE and clustering with the HDBSCAN algorithm. The visualization highlights the formation of two main clusters, visually distinct, which suggests the model's ability to discriminate contrasting patterns in the spectrograms. Additionally, the presence of sparse data regions may indicate the existence of uncaptured subgroups or, alternatively, insufficient data representativeness in certain areas of the latent space.

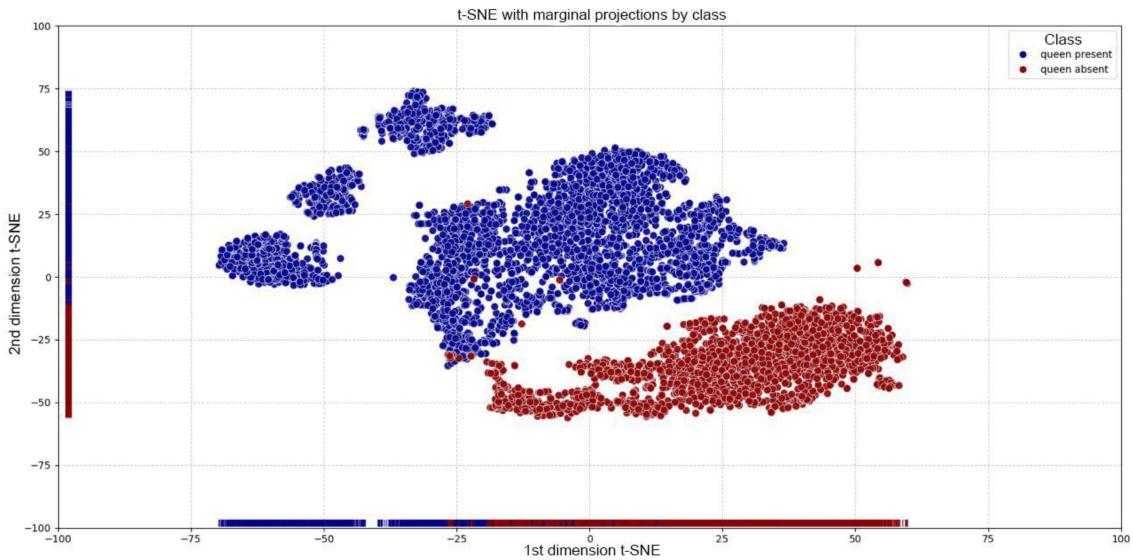

Figure 3. Projection of latent embeddings reduced with t-SNE and clustered with HDBSCAN.

Figure 4 displays characteristic samples of acoustic signals from hives with and without the presence of the queen bee. Subtle yet distinctive differences are observed in the spectral signatures. The queen presence condition tends to present a more complex energy distribution in the lower frequency bands, while the queen absence condition exhibits a simpler pattern. These variations form the basis upon which the model must learn to discriminate between the two hive states.

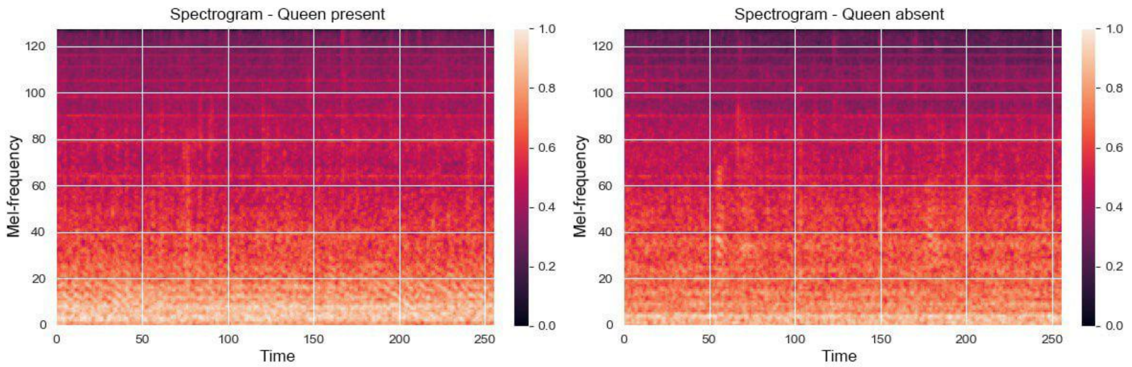

Figure 4. Spectrograms of audio recordings from the Nolasco et al. (2019) dataset [Nolasco et al. 2019b].

To ensure the discovery of an optimal and meaningful clustering structure, a hyperparameter optimization process for HDBSCAN was conducted. The configuration that presented the best performance was established with a minimum cluster size (`min_cluster_size`) of 50, ensuring that only clusters with a substantial number of points were considered, and a minimum samples per neighborhood (`min_samples`) of 12, to refine density detection. The quantitative evaluation of this configuration was performed using a set of cluster validation indices. The results revealed a multifaceted scenario: while the Silhouette Score (**0.121**) which suggests moderate cohesion and separation. The Calinski-Harabasz Index achieved a high value of **373.8** and is particularly noteworthy, as it indicates that the clusters are compact and well-separated in terms of their variances. Additionally, the Davies-Bouldin Index recorded **1.823**. Therefore, despite the indication of proximity between some points from different clusters (suggested by the Silhouette score), the overall structure of the partition is considered robust and statistically significant.

The quantitative evaluation of the model's ability to predict the queen presence was performed through clustering accuracy. To mitigate the absence of labels for points classified as noise by HDBSCAN, the k-Nearest Neighbors (kNN) algorithm was applied for class assignment. The final model achieved an accuracy of **98.78%**, as detailed in the confusion matrix presented in Figure 5. This result demonstrates remarkable performance, even surpassing robust supervised approaches proposed in the literature for the same task. For example, in a reference study, they achieved a maximum accuracy of **96%** in a hive-independent cross-validation experiment, using supervised approach based on Convolutional Neural Networks (CNN) and summarized spectrograms [Orlowska et al. 2022, Santos et al. 2025].

These results corroborate the effectiveness of the proposed unsupervised approach, demonstrating that, even in the absence of explicit labels during the training phase, the model was able to learn relevant latent representations for distinguishing between hives with queen present and queen absent.

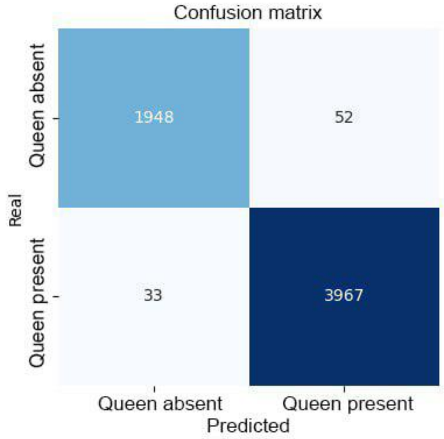

Figure 5. Confusion matrix with final classification results.

4. Conclusion

Here we propose an unsupervised deep learning method to identify beehives with or without queen based solely on the sounds they produce, achieving 98.78% accuracy. The proposed unsupervised detection approach eliminates the need for manual labeling, which considerably reduces the workload for specialists and beekeepers. It is also possible to detect unexpected patterns: algorithms such as autoencoders and HDBSCAN identify clusters and anomalies without prior definition, revealing acoustic signals that might not have been considered otherwise. Furthermore, our method easily adapts to new conditions, adjusting to recordings of bee colonies in different environments, species, or noise levels without requiring rework in data annotation.

This paper focuses on acoustic monitoring of real honeybee colonies in a data-intensive Science context, aligning closely with the goals of BreSci 2025. It demonstrates how data-driven AI techniques applied to audio signals can support scientific investigations with broad scalability. By automating the analysis of bee colony sounds, our approach contributes to e-Science in precision beekeeping, promoting faster, evidence-based decisions and fostering collaboration among beekeepers, animal scientists, engineers, and computer scientists.

We recognize two main limitations in this study: the relatively small dataset and variability in recording conditions, such as background noise and differences between colonies. These factors may limit the model's ability to generalize. To address this, we propose expanding the dataset to include more hives, different bee species (such as Brazilian native bees), and recordings under diverse environmental conditions. We also recommend developing automated processing pipelines, integrating cloud-based platforms, and conducting field tests in collaboration with beekeepers to validate real-world performance and encourage multidisciplinary engagement.

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