An Acoustic Signal Processing System for Identification of Queen-less Beehives

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***Abstract* — This paper proposes a machine learning system for identification of queen-less beehives by using audio signal enhancement methods and neural networks. In the proposed system, noisy audio signals captured from beehives are enhanced by using a Wiener filter; Improved Mel-frequency Cepstrum Coefficient (IMFCC) of the enhanced signals are then extracted and fed to a neural network. The result shows that the application of the proposed filter can improve the classification accuracy by at least 12%. The classification accuracy depends on the SNR of the input audio signal.**

INTRODUCTION

Apiculture has become one of the primary industries in New Zealand since beekeeping was started in this country around 180 years ago [1]. New Zealand honey is a popular and internationally known product. The most famous variety of New Zealand honey, Manuka honey caused a world sensation in 1991 when Bill Floyd, who coined the term Unique Manuka Factor (UMF), introduced it into the American market. For many years, New Zealand has been among the top 10 honey producers in the world, with more than 20,000 tons of production [2]. The honey annual export value has almost reached 350 million New Zealand Dollars (NZD). Unfortunately, the excellent benefits of Manuka honey and noticeable development of Apiculture increases not only market competition but also production cost. For example, selecting a well performing breeder queen bee costed 600 to 2,000 NZD in 2016 and 2017, while it costed 3,000 to 5,000 NZD in 2017 and 2018. The rentals of apiaries also grew by 40% in the same period. In this situation, New Zealand beekeepers have had to manage their resources efficiently to cope with market challenges.

Based on affordable application of Artificial Intelligence (AI), Data Science, Data Mining, Internet of Things (IoT), and other cutting-edge computing technologies, precision beekeeping has been proposed to monitor beehives intelligently and precisely. Obviously, the ultimate goal of precision beekeeping is to reduce production cost and increase the efficiency of beekeeping procedures. Data-driven beekeeping in addition to manual care is an inevitable result of fierce competition and technological development in this promising industry. Various types of data can be collected from beehives and fed to appropriate computing platforms, where the system can identify the health condition of beehives and send alarms or notifications to the beekeeper, for example through cellular phones.

Various methods based on using different physical quantities, such as acoustic noise (audio signal), temperature, video, weight, vibration, number of bees, humidity, and O2/CO2 content, have been developed to prove the feasibility of precision beekeeping. Among these methods, those use audio signals are very popular among researchers. This is because the most common communication form for bees is the vibration of wings which produce a sort of acoustic noise. Many audio-based beehive monitoring methods are still in the development phase and have not been introduced to the industry in practice. There are still many challenges to be dealt with because of the existence of many unknown components in the audio signals captured inside beehives and complicated nature of such signals. In the audio-based beehive status monitoring systems proposed so far, it is usually assumed that the audio signal maintain a high Signal-to-Noise Ratio (SNR).

In this paper, we propose a simple technique for enhancing the audio signals captured from beehives by using Wiener filter theory. Then, we extract the features of the enhanced signal by calculating Mel-Frequency Cepstral Coefficients (MFCC). Finally, we develop a Multi-Layer Perceptron (MLP) neural network to determine the existence of the queen in the beehive from the extracted features.

AUDIO-BASED BEEHIVE STATUS MONITORING

According to previous research of beehive sound monitoring [3-7], it is shown that a queen-less beehive can be identified by analysing an audio signal captured inside the beehive. However, they did not look at this problem in a real-life scenario where the captured audio signal is highly corrupted by environmental noise. In this section, we briefly review existing audio-based beehive status monitoring systems and motivate the need for improving existing systems.

A. *Acoustic signal processing*

In 2015, Wehmann et. al studied different acoustic signals generated by honey bees including hissing, buzzing, queen quacking, and piping. For their study, they developed and used an experimental system named Automatic Performance Index System (APIS) [4]. They captured an audio signal from the beehive when the system released stimuli in the beehive, for example, odours and electric shocks. The results showed that bees generated hissing like acoustic noise when they felt any change in carbon dioxide concentration or they felt any electric shocks.

In 2018, Kulyukin et. al compared deep learning and standard machine learning in classifying beehive audio samples [5]. They proved that a CNN which was used to classify acoustic spectrogram performed better than other four different machine learning methods. The hardware used in this research was BeePi which was a multi-sensor Electronic Beehive Monitoring (EBM) system. BeePi consists of Raspberry Pi, a mini camera and a microphone splitter, and several omnidirectional microphones with a frequency range between 15Hz and 20KHz. It includes a rechargeable battery charged by a solar panel. The microphone was placed at the entrance of the beehive to capture a 30-seconds audio signal every 15 minutes. This research successfully classified the audio signals into three categories: bee buzzing, crickets, and background noises. However, they didn't consider health or status monitoring of the beehives and they assumed that the audio signal is noise free.

In 2019, Antonio et. al proposed a method for detecting queen-less beehives by using acoustic signal processing [7]. The audio signal was acquired by omnidirectional microphones which were embedded in beehives and then were processed by an algorithm based on Logistic Regression (LR) model. Via extracting and comparing the MFCC features of the bee sound, two queen-less states of bee colonies were successfully detected and classified. The highlights of this study were that it used Singular Value Decomposition (SVD) to visualise and to compare the data acquired from beehives with different conditions. This avoided the incomplete interpretation of the bee's behavior when the data of only one colony was analysed.

The raw bee sound signals recorded from a beehive are the mixture of the sound contributed by each bee of the colony [7]. They can be regarded as a set of continuous low-frequency signals with high density. In the real beekeeping environment, however, the raw sounds contain the bee sound mixture and other noises that can be called non-bee sounds. The non-bee sounds are the ambient noises, such as human voice, engine roaring, rain noise, and wind noise. The raw sounds need to be annotated by labelling the data according to the features extracted from the pure bee sounds and the external acoustic samples. The segmented acoustic signals can be processed by the labels and then classified by an appropriate machine learning algorithms.

The most intriguing finding of the previous studies can be summarized as a table illustrating the relationship between the types of bee sound signals, their frequencies, the signal patterns, the senders, and the possible activities the bees will do. Such table is shown in Table 1. Based on this table [8], a remote monitoring system was designed to detect the pest infestation in bee colonies by comparing the sound fingerprints between healthy and infected beehives. This research used three algorithms to make the comparison, including Support Vector Machines (SVM), Linear Discriminant Analysis (LDA), and Principle Component Analysis (PCA). The outcome showed that SVM and LDA had better experimental performance than PCA.

	Frequency (Hz) signal	**Pattern**	**Sender**	**Possible Activities**
Tooting	300 ~ 500	Pulse sequence	Queen	Prevent hatching of further queens and trigger quacking
Quacking	300 ~ 350	Pulse sequence	Queen	Presence detection, viability of confined queens
Hissing	300 ~ 3600	Single sequence	Colony	Warning signal
Piping	100 ~ 2000	Single sequence	Scout	Triggers colony hissing, prepare for swarming
Recruit	200 ~ 350	Pulse sequence	Scout	Existence and quality of valuable food source

Table 1 The relationship between bee's audio signals and activities [8]

B. *Audio-based queen-less beehive identification*

In 2013, Duran et. al looked at identification of queen-less bee colonies from beehive audio signal [9]. They considered two physical features of beehive audio signal indicating the queen presence, which are called "warble" and "moaning". The warble, which occurs in the frequency range between 225 to 285Hz, is a signal of inactivity of the queen bee. The moaning, which is in the range between 165 to 285Hz, shows the absence of the queen bee in a bee colony. This study proved that the signals of queen-less beehive were prominent in low frequencies when using Short-time Fourier Transform (STFT) and S-transform Spectrogram. Compared with STFT, S-transform can deal with the non-stationary signals appearing in the beehives.

In 2019, Antonio et. al analysed patterns of the audio signal acquired from beehives by Lasso Logistic Regression (LLR) and Singular Value Decomposition (SVD) for identifying queen-less colonies [6]. Their study consisted of two aspects, the identification of the queen-less state and the classification of three different queen-less situations, a queenright colony, a queen-less colony in a natural way, and a healthy colony with a queen bee artificially removed. For the purpose of comparing and accessing the bee health status in these colonies, five beehives were used to implement two sessions of the experiment. The five beehives included two healthy colonies with a large population, two healthy colonies with a regular population, and one queen-less colony with a reduced population. The queen bees of two healthy colonies were removed (one with a large population and one in regulation). The classification was conducted by Logistic Regression with Lasso regularisation using the *glment* package in R, which provided the probability of the three-class outcomes. The dataset was partitioned into training and testing dataset (70% and 30% respectively), and the result of classification was showed as binary models returning the distinct features of all the classes. The Area Under Curve (AUC) of Receiver Operating Characteristic Curve (AOC) was calculated to evaluate the algorithm performance, and it showed that its accuracy was above 95%.

In 2019, the Hilbert Huang Transform (HHT) was combined with Machine Learning (ML) applications to improve the design of spectral representation in long-term modelling [7]. This study used an actual audio dataset achieved from the NU-Hive project and two ML classification algorithms, which were SVM and Convolutional Neural Network (CNN), to recognise beehive statuses. The classification experiments compared the performance between SVM and CNN. Via five times of experiments with different sample settings. The best performance of SVM showed a high AUC score which was generated by inputting audio samples with the sample size of 20 MFCC produced by the mean of MFCC coefficients in every ten minutes with the maximum frequency at 6,000 Hz. In comparison, the results of the CNN method showed its contribution to tackling the problem of the “hive-independent” dataset, which means the training and testing datasets were acquired from different beehives.

A common problem with the methods discussed above is that they usually assume the audio signal is noise-free. The noisy audio signal can reduce the classification performance significantly.

Proposed System

The first part (algorithm) of the proposed system includes a signal enhancement algorithm that improve the SNR of the audio signal captured inside a beehive. The Wiener filter theory is used to remove the noise in the time domain. Then, the improved MFCC of the enhanced signal are extracted as the feature of the input audio signal. Finally, the extracted features are fed to a neural network that determine the presence or absence of the queen bee. An increase in the classification accuracy is expected after using the proposed system, such that the system can operate in real-life situations where the audio signal captured inside the beehive is highly corrupted by ambient noise.

A. Proposed Signal Enhancement Algorithm

The FIR Wiener filter is chosen to remove noise from the noisy signal in the time domain **错误!未找到引用源。**. The central part of configuring FIR Wiener filters is to compute the optimal filter coefficient. Firstly, the size of the linear matrix equation is set as 100 × 100. The performance of signal enhancement can be improved with the enlargement of the size, but the cost of calculation also increases. The optimal solution of the Wiener filter can be defined as:

$$h_{opt} = R_{yy}^{-1} r_{yd}^{-1} \qquad (1)$$

Where, $R_{yy}(n)$ is the autocorrelation matrix of the observed signal y and $r_{yd}(n)$ is the cross-correlation matrix between the observed and the desired signals. In the next step, these two matrices must be calculated.

Matrix $R_{yy}(n)$is calculated by the Toeplitz matrix function in MATLAB:

$$R_{yy}(n) = toeplitz\left(xcorr\left(observed_{signal}\right)\right) \qquad (2)$$

The cross-correlation matrix between the observed and the desired signals $r_{yd}(n)$ is calculated by $xcorr()$ function in MATLAB:

$$r_{yd}(n) = xcorr\left(desired_{signal}, observed_{signal}\right) \qquad (3)$$

Then the optimal filter coefficient h_{opt} is used to filter the noisy signals.

B. IMFCC features

The MFCC is the most popular measure to represent features of speech and other audio signals, but it is sensitive to the noise interruption, as mentioned above. In this case, the MFCC should be improved for the application of interest. It can be seen that the improved MFCC provides the classifier with a feature vector closer to the original signal’s. As the noise increases, the classification accuracy rate based on the traditional MFCC features drops sharply, while those based on the Improved MFCC features still maintain a high classification accuracy rate [10]. The MFCC features of the signal filtered by Multi-band Spectral Subtraction and Wiener filter can improve the features of the audio signals so that this type of MFCC can be called “Improved Mel-frequency Cepstral Coefficients (IMFCC)”. With the filtered signal, the features extracted are closer to that of the original signal. The IMFCC shows a better recognition rate of the target sound in noisy environments. Another advantage of IMFCC is that it considers the varying interference in different bands. For example, the rain noise is more prominent in the low-frequency range. The interference of rain noise at low frequencies leads to the inappropriate feature extraction, which may decrease the classification accuracy of the queen-less signal. The IMFCC, however, extracts features of the signal in each Mel-frequency band to improve the feature expression of the queen-less signal.

The calculation of IMFCC feature extraction has six steps as following (The workflow of the IMFCC feature extraction is shown in Fig. 1):

1) Pre-emphasis

The pre-emphasis filter with the coefficient as 0.97 is applied to amplify the high frequencies in the observed signals. Because the higher the frequency is, the more serious the loss of audio energy will be, increasing the amplitude of the signal in high frequency can make feature extraction more representative.

2) Framing and window

The output audio signal from Multi-band Spectral Subtraction and Wiener filter is framed into 20ms frames. The

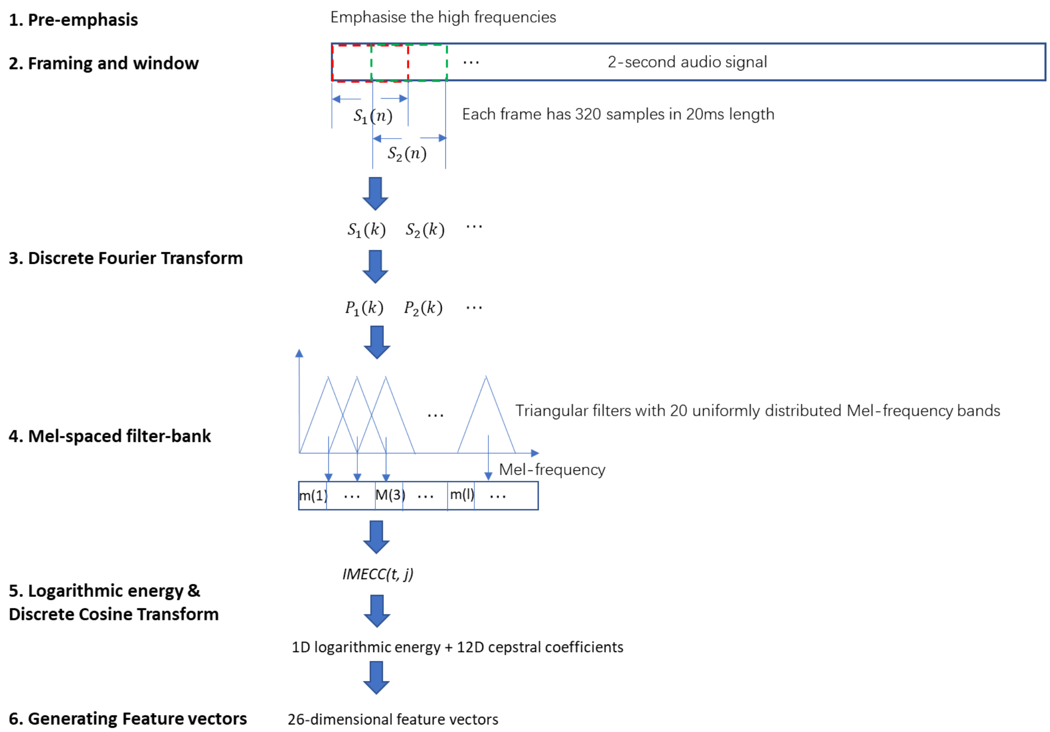

Fig. 1 The workflow of the IMFCC

frame size is set to 10ms in the noise filtering step for smoothing the signals to be processed, and it can save some computing resources to be 20ms in this step. Each frame length is 0.02×16000 = 320 samples. The frame step is set to 10ms, which allows 50% overlapping of two adjacent frames, which avoids signal distortion. The first set of 320 samples begins with the 1st sample, and the next starts at the 161st sample. It does not stop until the end of the signal.

3) Discrete Fourier Transform

Because the transformation of the audio signal in the time domain is usually challenging to see the characteristics of the signal, it is usually converted into an energy distribution in the frequency domain. Different energy distributions can represent the characteristics of different audio signals. The power spectrum estimation of the framed signals can be calculated by:

$$P_i(k) = \frac{1}{N}|S_i(k)|^2 \tag{4}$$

4) Mel-spaced filter-bank

This is a set of 20 triangular filter banks that filter the power spectrum estimates of the periodic graph obtained in the previous step. The Mel-spaced filter-bank consists of 26 filter vectors with a length of 257. Most of the 257 values of each filter are 0, and only non-zero for the frequency range that needs to be collected. The input signal of 257 points will pass through 26 filters, and the energy of the signals passing through each filter can be calculated.

5) Logarithmic energy and Discrete Cosine Transform

The Logarithm of 26 energies are calculated, and then 26 cepstral coefficients are obtained by performing DCT on the 26 energies of the signals. Twelve numbers from two to thirteen are reserved, which are called MFCC features. It is added by 1D Logarithmic energy to show the features of each frame.

6) Generating the IMFCC features

Finally, the difference of cepstral coefficients is added to represent the dynamic change of the cepstral coefficients over time. The M value is set as 2, plus the first-order difference operation to produce 26-dimensional feature vectors.

$$\Delta C_m(t) = \frac{\sum_{-M}^{M} C_m(t+\tau)\tau}{\sum_{-M}^{M} \tau^2} \tag{5}$$

The 26-dimensional feature vectors are the input of the Multi-Layer Perceptron to do Queen-less and Queenright classification. In the next section, the performance of IMFCC and denoise techniques will be shown.

C. *Multi-Layer Perceptron*

Multi-Layer perceptron (MLP) is generally called Artificial Neural Network (ANN). It is a fundamental and popular classification algorithm for Deep Learning. Usually, the MLP has at least three layers—the first layer called the input layer, the last layer called the output layer, and the middle layer called the hidden layer. The original data are fed into the input layer, and the expected output can be taken from the output layer. The number of the hidden layers can be increased to make a more complicated model according to the tasks given.

The hidden layers of the MLP model include many neurons that are connected to other neurons in the previous and next layers. The advantage of this structure is that all neurons calculate each input with different weights and bias at the hidden layers. The more neurons and layers are in the model, the higher accuracy the model calculates. The input is passed to each neuron next layer, calculated with the weights and bias and activated by the activation function. Its output is the input of the next layer, and the calculation process repeats until the output layer. This process is called feedforward. The loss (or error) is calculated at the output layer, and the loss will be minimised by using backpropagation method where the weights and the biases are updated to update the output [12]. The purpose of this is to make the output closer to the actual value (as shown in Fig. 2).

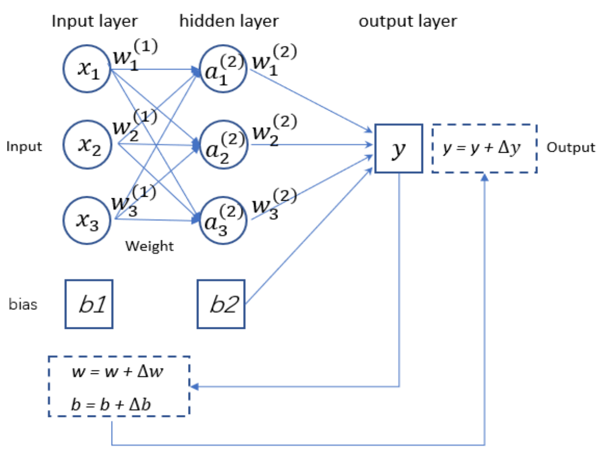

Fig. 2 The MLP model update the output y to make it closer to the true value by using feedforward, loss calculation, and backpropagation methods

The MLP model has several activation functions. The sigmoid function can generate a smooth gradient because it can quickly get the derivative. It also bound the output value in a range between 0 and 1, which makes the output as a probability explanation more straightforward and more intuitive. However, it has vanishing gradient problem. The tanh function is an improvement version of the sigmoid function. It is a rescaled sigmoid function lying between -1 and 1. This benefits that the mean values of the tanh function are always around zero, while that of the sigmoid can be varies depending on the input values. Another advantage is that the tanh function can map strongly negative input to negative output, but sigmoid will generate the output close to zero, which can reduce the weight updating speed in backpropagation. This feature enables the tanh function to be suitable for processing bee audio signals because the feature vectors of bee sound possessing lots of negative values.

Gradient Descent (GD) is the most popular method to minimise the cost function of an MLP model, but it has some drawbacks. One of its main disadvantages is that GD requires much manual work to find out the optimisation parameters of the algorithm, for example, the learning rate and convergence standard. The typical way to do this is to run the algorithm with different parameters, and the model with "the best" performance is picked out, which means the computing consumption of optimisation procedure is expensive. Compared with GD, the Limited memory Broyden–Fletcher–Goldfarb–Shanno (L-BFGS) method, which is an optimiser in the family of quasi-Newton methods, is more appropriate to train and to inspect convergence.

The architecture selection is another method to optimise an MLP model. The sensitivity analysis method based on derivatives mainly uses derivatives to evaluate the influence of input variables on output. When the derivative of a neuron approaches zero, the mean value and variance of the neuron are small and the neuron can be deleted. The architecture of the MLP model can be streamlined by deleting these negligible neurons in each layer of the model[13].

The selections of an activation function, an optimiser and the architecture are the elements of the MLP model optimisation. The difference between the classification performance of an unoptimised MLP model and an optimised MLP model is shown in next section.

RESULTS

A. *The noise impact on classification performance*

We implemented the propose system as described in the previous section by using Python. The initial results showed the classification accuracy dropped dramatically when the input audio signal is noisy (which is usually the case in real-life situations). The configuration of the MLP classification model is shown in Table 2.

Parameter	**Setting**
Number of hidden layers	2
Number of hidden neurons	5, 2
Activation function	Tanh
Solver	L-BFGS

Table 2 The configuration of MLP classification model

It can be seen from Table 3 that the classification accuracy of the input signal with the SNR of 10dB was almost 30% lower than that of the clean signal.

	Clean bee signal	**Noisy signals**		
		40dB	**20dB**	**10dB**
Classification accuracy	89.83%	80.33%	73.33%	60.83%

Table 3 The comparison between the classification of the clean bee signal and the noisy signals with different SNR.

Classification accuracy of around 60% is unacceptable for the queen-less beehive monitoring because it will provide wrong information about the bee statuses to the beekeepers. The next section shows the performance of processing the enhanced signal.

B. *Signal enhancement*

The signals enhanced by the Wiener filter reduced the noise composition from the noisy signals. Through the SNR calculation of the noisy signals and the enhanced signals, it showed that the SNRs of signals enhanced by the Wiener filter rose by approximately 4dB, 16dB, and 23dB respectively. The exciting finding was that the smaller the SNR of the noisy signal was input, the better the noise reduction effect of the Wiener filter performed (as shown in Table 4).

Signal enhancement effect	
Input SNR	**Output SNR**
40dB	44.06dB
20dB	35.63dB
10dB	32.82dB

Table 4 The comparison between the SNR of the noisy signal before and after the Wiener filter.

The classification performance of the enhanced signal was much better than noisy signals. The result showed that the classification accuracy increased by Wiener filter were around 12%, 17%, and 29%, respectively. The classification accuracy of the MLP for the enhanced signals were approximately 90%, which showed that the signal enhancement effect of Wiener filter kept excellent and stable for input signals with high SNR in this experiment (as shown in Table 5).

Classification accuracy		
Input SNR	**Only MLP**	**Wiener filter + MLP**
40dB	80.33%	92.61%
20dB	73.33%	90.78%
10dB	60.83%	89.77%

Table 5 The comparison between the classification accuracy of the noisy signal before and after the Wiener filter.

C. *MLP model optimisation*

An optimised MLP model was designed to compare with an unoptimised MLP model. An unoptimised MLP model used default settings which has just two hidden layers with five and two units respectively. The activation function used sigmoid, and the solver (Minimising the cost function) used GD (Gradient Descent algorithm). The optimised MLP model has three layers with ten, five, and three units, respectively. The tanh function is used for activation, and the L-BFGS is used for minimising the cost function. The setting of the main parameters of the two MLP models is shown in Table 6.

Parameter	**MLP model Setting**	
	Unoptimised	**Optimised**
Number of hidden layers	2	3
Number of hidden neurons	5, 2	10, 5, 3
Activation function	Sigmoid	Tanh
Solver	GD	L-BFGS

Table 6 The configuration of the two MLP models

The input is the feature vector of signals enhanced by Wiener filter		
Input	**Unoptimised MLP model**	**Optimised MLP model**
Feature vector of 40dB enhanced signal	48.50%	97.33%
Feature vector of 20dB enhanced signal	48.33%	97.06%
Feature vector of 10dB enhanced signal	48.44%	95.50%

Table 7 The comparison between classification accuracy of an unoptimised and an optimised MLP models

The result (as shown in Table 7) showed that the classification accuracy of an optimised MLP model was around 49% higher than an unoptimised one.

D. *Comparison between MLP and other common models*

The noisy signal was processed by KNN, SVM and proposed MLP model to show the difference between the performance of conventional models and proposed one. The results showed proposed model has higher classification accuracy and degree of separability(as shown in Table 8 and 9).

Classification accuracy			
Input SNR	**KNN**	**SVM**	**Wiener filter +MLP**
40dB	82.66%(K=13)	72.00%	97.33%
20dB	75%(K=16)	68.00%	97.06%
10dB	60.33%(K=7)	60.00%	95.50%

Table 8 The comparison between classification accuracy of KNN, SVM and proposed MLP models

AUC score			
Input SNR	**KNN**	**SVM**	**Wiener filter +MLP**
40dB	**0.9**	**0.84**	**0.98**
20dB	**0.84**	**0.78**	**0.98**
10dB	**0.64**	**0.58**	**0.98**

Table 9 The comparison between classification accuracy of KNN, SVM and proposed MLP models

CONCLUSIONS

In conclusion, the contribution of this study is to propose an improved audio-based method for queen-less beehive identification from noisy signal. This method proves to greatly improve the classification accuracy of the queen-less beehive. The Wiener filter enhanced the bee audio signals by increasing 4dB to 23dB SNR of the noisy signals. The MLP classification model with Tanh activation function and L-BFGS solver rose the queen-less classification accuracy by 12% to 29% by using the IMFCC features of the enhanced signals. Optimisation of the MLP model can dramatically increase the classification accuracy. Based on this experimental settings, the MLP model with Tanh activation function and L-BFGS solver performed around 97% classification accuracy of the queen-less beehive, approximately 49% higher than the model with Sigmoid activation function and GD solver. Compared with KNN and SVM, proposed MLP model showed better performance evaluated by classification accuracy and AUC score.

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