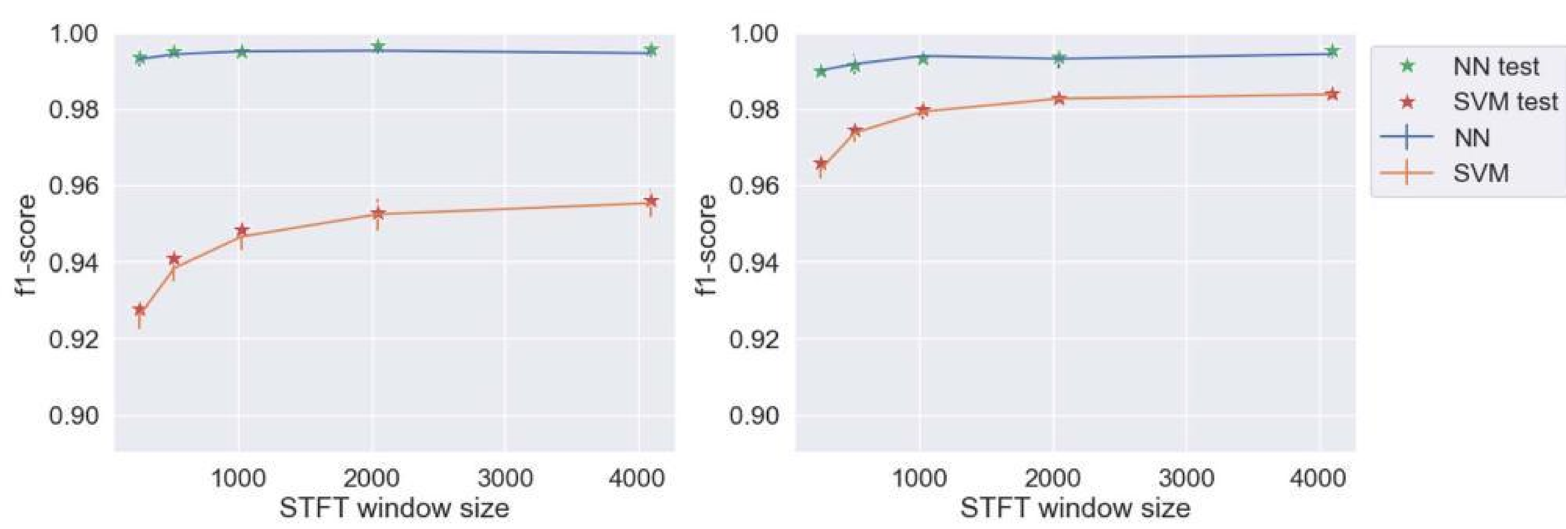

Fig. 9. Crossvalidation and final test results changing the window size of the STFT features. On the left using only dataset 1 and on the right combining dataset 1 and dataset 2.

TABLE VI
ACCURACY AND F1-SCORE WITH NN AND DIFFERENT FEATURES

Feature parameter	Accuracy	Accuracy test	F1-score	F1-score test
mfcc 10	0.9429 ± 1.94E-03	0.9419	0.9596 ± 1.51E-03	0.9586
mfcc 20	0.9758 ± 2.73E-03	0.9751	0.9828 ± 1.87E-03	0.9820
mfcc 30	0.9862 ± 1.89E-03	0.9829	0.9901 ± 1.35E-03	0.9877
mfcc 40	0.9889 ± 1.48E-03	0.9900	0.9920 ± 1.09E-03	0.9928
mfcc 50	0.9906 ± 1.75E-03	**0.9918**	0.9933 ± 1.27E-03	**0.9941**
stft 256	0.9862 ± 1.72E-03	0.9862	0.9902 ± 1.25E-03	0.9900
stft 512	0.9885 ± 3.88E-03	0.9884	0.9918 ± 2.74E-03	0.9916
stft 1024	0.9915 ± 1.64E-03	0.9910	0.9939 ± 1.18E-03	0.9935
stft 2048	0.9904 ± 3.59E-03	0.9913	0.9932 ± 2.55E-03	0.9937
stft 4096	0.9921 ± 1.61E-03	**0.9935**	0.9944 ± 1.14E-03	**0.9953**

The bold values are the best results obtained for that experiment, and for the two metrics "accuracy" and "f1-score".

TABLE VII
ACCURACY AND F1-SCORE WITH SVM AND DIFFERENT FEATURES

Feature param	Accuracy	Accuracy test	F1-score	F1-score test
mfcc 10	0.9280 ± 1.79E-03	0.9279	0.9483 ± 1.25E-03	0.9477
mfcc 20	0.9680 ± 1.42E-03	0.9698	0.9770 ± 1.05E-03	0.9781
mfcc 30	0.9830 ± 1.13E-03	0.9835	0.9878 ± 8.32E-04	0.9880
mfcc 40	0.9879 ± 1.14E-03	0.9881	0.9913 ± 8.15E-04	0.9914
mfcc 50	0.9908 ± 1.19E-03	**0.9908**	0.9934 ± 8.46E-04	**0.9933**
fft 256	0.9502 ± 3.17E-03	0.9534	0.9641 ± 2.38E-03	0.9661
fft 512	0.9635 ± 3.26E-03	0.9652	0.9737 ± 2.43E-03	0.9747
fft 1024	0.9712 ± 2.74E-03	0.9723	0.9793 ± 2.03E-03	0.9799
fft 2048	0.9760 ± 2.18E-03	0.9764	0.9828 ± 1.60E-03	0.9829
fft 4096	0.9775 ± 1.83E-03	**0.9783**	0.9838 ± 1.36E-03	**0.9843**

The bold values are the best results obtained for that experiment, and for the two metrics "accuracy" and "f1-score".

the feature extraction that will require more time to be computed and also more memory to store them temporarily during the computation. So it is important to find a tradeoff between the required accuracy of the predictions and the hardware resources that can be very limited in case of IoT devices that in most of the cases are microcontrollers powered by a small battery that should last for months or years before the replacement.

IV. CONCLUSION

The results indicate that larger classifier models exhibit greater accuracy in detecting the presence of the queen bee. However, it is noteworthy that these models also demand more computational resources making them less practical for IoT applications. In scenarios where edge computing on small battery-powered devices is essential for extended operational periods, smaller classifiers may be more suitable despite a potential decrease in accuracy.

We can notice also the importance of having an extensive number of datasets to generate models that are not specific to a particular beehive but can adapt to others as well. In this work, we observed that having data from different hives slightly reduces accuracy but enhances generalization capabilities of the classification models. The size of the audio files also has a significant effect on the accuracy of the machine learning models used. Here, it is necessary to find a compromise between prediction accuracy and the memory space used to record the audio, which also leads to an increased number of computations needed to process and extract features.

Lastly, information compression into a reduced number of values is essential. This allows for a reduction in the complexity of the classifier model without losing too much information and degrading performance excessively. Overall, the findings demonstrated superior performance when employing STFT compared to MFCC features. However, this improvement comes at the expense of increased memory demands for storing such data on a potential IoT device. This suggests the necessity for a trade-off, coupled with the implementation of effective feature selection techniques.

In summary, the research emphasizes the efficacy of audio-based methods for detecting the queen bee in beehives. While larger classifiers offer superior accuracy, their resource-intensive nature poses challenges for IoT applications. Achieving a balance between accuracy and resource efficiency is crucial in these contexts, making smaller classifiers more practical for prolonged operational periods without sacrificing essential detection capabilities.

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