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Automatic Diagnosis of Snoring Sounds with the Developed Artificial Intelligence-based Hybrid Model

Muhammed YILDIRIM[1*]
[1] Department of Computer Engineering, Faculty of Engineering and Natural Sciences, Malatya Turgut Ozal University, Malatya, Turkey
[*1] muhammed.yildirim@ozal.edu.tr

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Abstract: Sleep patterns and sleep continuity have a great impact on people's quality of life. The sound of snoring both reduces the sleep quality of the snorer and disturbs other people in the environment. Interpretation of sleep signals by experts and diagnosis of the disease is a difficult and costly process. Therefore, in the study, an artificial intelligence-based hybrid model was developed for the classification of snoring sounds. In the proposed method, first of all, sound signals were converted into images using the Mel-spectrogram method. The feature maps of the obtained images were obtained using Alexnet and Resnet101 architectures. After combining the feature maps that are different in each architecture, dimension reduction was made using the NCA dimension reduction method. The feature map optimized using the NCA method was classified in the Bilayered Neural Network. In addition, spectrogram images were classified with 8 different CNN models to compare the performance of the proposed model. Later, in order to test the performance of the proposed model, feature maps were obtained using the MFCC method and the obtained feature maps were classified in different classifiers. The accuracy value obtained in the proposed model is 99.5%.

Key words: Deep Learning, Classifiers, CNN, MFCC, Snoring, Spectrogram

Geliştirilen Yapay Zeka Tabanlı Hibrit Model ile Horlama Seslerinin Otomatik Teşhisi

Öz: Uyku düzeni ve uyku devamlılığı insanların yaşam kalitesi üzerinde büyük bir etkiye sahiptir. Horlama sesi hem horlayanın uyku kalitesini düşürür hem de çevredeki diğer insanları rahatsız eder. Uyku sinyallerinin uzmanlar tarafından yorumlanması ve hastalığın teşhisi zor ve maliyetli bir süreçtir. Bu nedenle çalışmada horlama seslerinin sınıflandırılması için yapay zekâ tabanlı hibrit bir model geliştirilmiştir. Önerilen yöntemde öncelikle ses sinyalleri Mel-spektrogram yöntemi kullanılarak görüntüye dönüştürülmüştür. Elde edilen görüntülerin öznitelik haritaları Alexnet ve Resnet101 mimarileri kullanılarak elde edilmiştir. Her mimaride farklı olan özellik haritaları birleştirildikten sonra NCA boyut indirgeme yöntemi kullanılarak boyut indirgeme yapılmıştır. NCA yöntemi kullanılarak optimize edilen özellik haritası, İki Katmanlı Sinir Ağı'nda sınıflandırılmıştır. Ayrıca önerilen modelin performansını karşılaştırmak için spektrogram görüntüleri 8 farklı CNN modeli ile sınıflandırılmıştır. Daha sonra, önerilen modelin performansını test etmek için MFCC yöntemi kullanılarak öznitelik haritaları elde edilmiş ve elde edilen öznitelik haritaları farklı sınıflandırıcılarda sınıflandırılmıştır. Önerilen modelde elde edilen doğruluk değeri %99,5'tir.

Anahtar kelimeler: Derin Öğrenme, Sınıflandırıcılar, CNN, MFCC, Horlama, Spectrogram

1. Introduction

Quality sleep has a great impact on people's daily lives. While snoring that occurs during sleep reduces the sleep quality of people, it can be a precursor to some diseases. Snoring not only affects the snorer's sleep quality, but it also affects the sleep quality of those in the same environment [1]. Snoring is caused by the relaxation of the muscles surrounding the throat during sleep. Since the relaxation of the muscles surrounding the throat narrows the airway, the vibrations that cause snoring are triggered. Snoring is most common when you're lying on your back. It is possible to reduce the snoring problem by lying on its side, but it is not a sure solution [2, 3].

Snoring caused by severe sleep apnea has a 40% higher risk of death than other people. Snoring not only disturbs the people around us, it can also be a sign of serious diseases. Severe sleep apnea, stroke, heart diseases, reflux, fatigue, mental health problems, headache, and sexual reluctance are some of these diseases. Mild and moderate sleep disorders can also cause problems such as heart diseases and sexual reluctance [4-6].

It is of great importance to classify the sounds that people make during sleep in order to improve sleep quality. These sounds should be recorded under the control of a sleep specialist and diagnosed accordingly. This is a time-consuming, costly and difficult process. This study, it is aimed to develop a computer-assisted artificial

* Corresponding author: muhammed.yildirim@ozal.edu.tr ORCID Number of authors: [1] 0000-0003-1866-4721

intelligence-based hybrid model that will help the specialist to diagnose and classify voice data quickly. Thanks to this developed computer-aided system, snoring sounds will be classified more quickly and accurately.

1.1. Related Works

There are studies in the literature for the diagnosis of snoring sounds. Khan et al. [7] proposed a CNN-based model for the classification of snoring sounds in their paper. The data set used in the study consists of two classes, snoring and non-snoring. The researchers obtained an accuracy value of 96% in this study.

Jiang et al. proposed a LSTM-DNN-CNN based model to classify snoring sounds. In the study, feature extraction was performed with the Mel-spectrogram method. The researchers stated that they obtained an accuracy value of 95.07% in this study [8].

Cavusoglu et al. developed a new data set to classify snoring and non-snoring sounds in their study. Feature extraction of the sound signals in the data set was performed using the Sub-band spectral energy method. The researchers classified the feature maps they obtained using the linear regression method. The accuracy value obtained in this study was 90.2% [9].

Dafna et al. used feature extraction methods such as MFCCs, LPCs, and SED in this study. The researchers classified the feature maps they obtained in the Adaboost classifier. In the study, a high accuracy value of 98.2% was obtained. The data set used in this study consists of two classes, snoring and non-snoring sounds [10].

In the method, they developed to classify snoring and non-snoring sounds in this study, Wang et al. obtained an accuracy value of 94.5% in the SVM classifier. In this study, different methods were preferred for feature extraction. The threshold method and linear and nonlinear feature extraction methods are some of them [11].

Lim et al. used recurrent neural networks to classify snoring and non-snoring sounds in their study. In this study, many methods were used for feature extraction. STFT and MFCC are some of these methods. In this study, the researchers obtained an accuracy value of 98.9% [12].

Arsenali et al., while classifying snoring and non-snoring sounds in their study, performed feature extraction using the MFCC method. The accuracy value obtained in this study, which was carried out using Recurrent Neural Networks, was 95% [13].

Shen et al. used MFCC, LPMFCC, and LPC methods for feature extraction while classifying snoring sounds in their study. The feature maps obtained using the MFCC method were classified in CNN and LSTM networks. When the feature map obtained using the MFCC method is classified in the LSTM network, an accuracy value of 87% was obtained [14].

1.2. Contributions and Innovations

- This study, it is aimed to classify snoring sounds, which is a serious problem today.
- Two different methods were used in the study. In the first, the feature maps obtained by the MFCC method were classified in different supervised classifiers.
- In the second method, a hybrid model is proposed. In the proposed model, first of all, sound signals were converted into images by the Mel-spectrogram method. Then, Alexnet and Resnet101 architectures were used as the basis and feature maps were obtained. The obtained feature maps were concatenated and different features of the same data were brought together.
- NCA size reduction method was applied to the combined feature map. In this way, since unnecessary features are eliminated, the training time of the model is shortened.
- In the final stage of the proposed hybrid model, the optimized feature map is classified in the Bilayer Neural Network.
- In the study, the feature map obtained using the MFCC method was classified in 6 different classifiers, and the images obtained using the Mel-spectrogram method were classified using 8 different pre-trained models. When the obtained results were evaluated, it was observed that the most successful model was the proposed hybrid model.
- In the proposed hybrid model, the accuracy value attained is 99.5 %. This result indicates that the proposed model can be utilized to diagnose snoring sounds.

1.3. Organization of Paper

In the first part of the paper, general information was given and the contribution and innovations of the study to the literature were discussed. In the second part, the material and methods section is examined, in this section the data set used in the paper, deep models, spectrogram method, classifiers, and NCA method are discussed. In addition, the hybrid model developed for the classification of snoring sounds is examined in this section. The results obtained using different methods and models are presented in the third part, the discussion section in the fourth section, and the conclusion section in the last part.

2. Material and Methods

In this section, the data set used in the paper, deep models, spectrogram method, classifiers, NCA, and the proposed hybrid model is examined. The rough diagram of the proposed hybrid model is given in Figure 1.

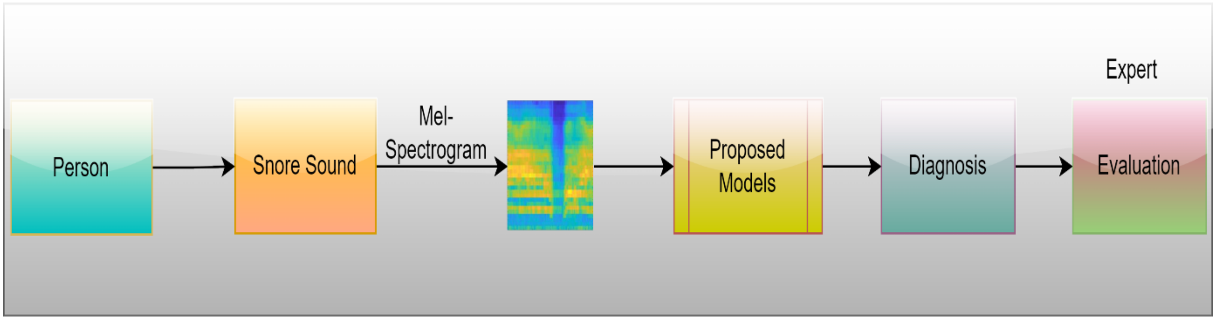

Figure 1. The rough working manner of the developed hybrid method

2.1. Data Set

A public data set was used in the study. The dataset used in the study consists of two classes, snoring and non-snoring. There are 500 sound files in each class. Each sound data is 1 second and these data have the extension ".wav" [7]. In Figure 2, sound data is shown as a signal.

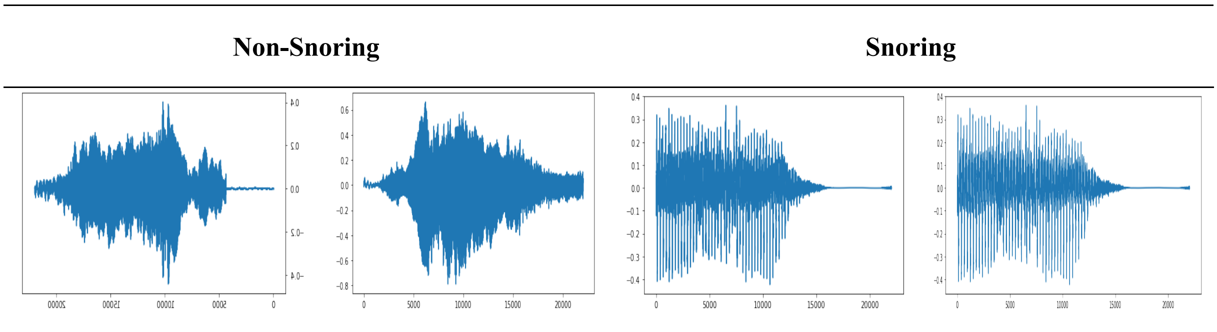

Figure 2. Examples of sound signals

While the first two images in Figure 1 belong to the Non-snoring class, the third and fourth images belong to the snoring class.

2.2. Spectrogram, Deep Models and NCA

The spectrogram is a visual heat map that represents the signal time on the horizontal axis and the signal frequency on the vertical axis as it changes with time. It is possible to define the spectrogram briefly as a visual representation of a time-varying sound signal [15, 16]. In this paper, the Mel-Spectrogram method was preferred to work with spectrograms of sound signals. Examples of spectrograms obtained using sound signals are presented in Figure 3.

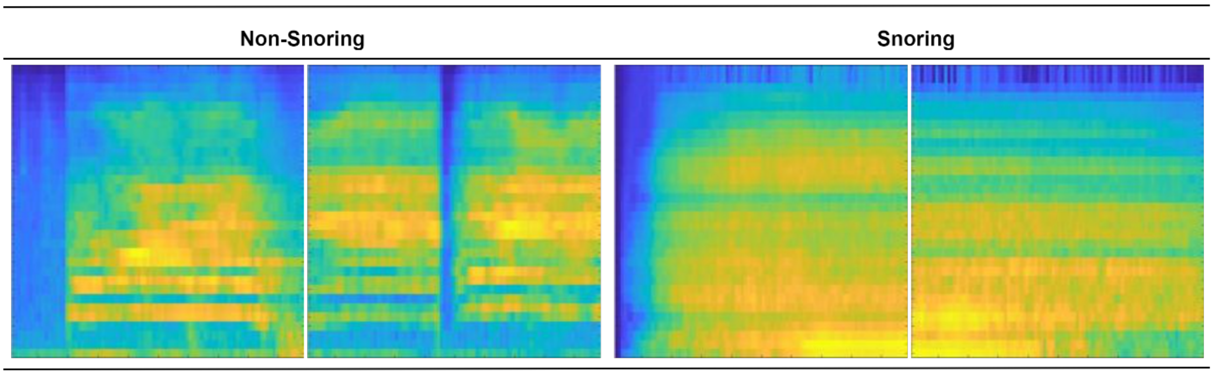

Figure 3. Spectrogram examples

In order to test the performance of the hybrid model proposed in the study, the obtained spectrogram data were also classified with deep methods accepted in the literature. 8 different deep methods were used in the paper. The first one is the Alexnet, which makes a great contribution to the popularity of deep learning. The Alexnet won the ILSVRC ImageNet competition in 2012 [17]. Darknet53 architecture is one of the current architectures of recent years. This architecture was developed based on the Darknet19 and Resnet architectures in YoloV2 [18]. In Resnet architecture, on the other hand, the gradient problem is tried to be solved by using Residual blocks. This model, created by He et al., was the winner of the ILSVRC ImageNet competition in 2015 [19]. The Densenet201 architecture developed by Huang et al. is different from other architectures in terms of the use of activation functions. The original data is maintained in all types of layers in the Densenet201 architecture, in addition to the activations from preceding layers [20]. Googlenet, which won the ILSVRC ImageNet competition in 2014, is another architecture employed in the study. This approach is one of the first to abandon the sequential arrangement of layers [21]. The Mobilenet architecture developed by Howard et al. is a architecture mostly suggested for mobile applications. In this model, the researchers aimed to develop a model with fewer parameters, high performance, and working speed [22]. The InceptionV3 model, developed by Szegedy et al., consists of 3 parts. This model has a convolution block, an initial block, and a classification block [23]. The last model used in the study is the Efficientnetb0 model. This model is a current and popular model developed in recent years. In this model, in addition to the depth factor, the concepts of width and resolution are also discussed for the first time [24].

NCA dimension reduction was preferred to reduce the size of the feature maps get in the proposed hybrid model. Thanks to the NCA dimension reduction method, unnecessary features in the feature map are eliminated. This step allows the training time of the proposed hybrid model to be completed in a shorter time [25, 26].

2.3. MFCC and Classifiers

While the first method used in the study is the spectrogram method, another method is the MFCC method. With the MFCC method, direct feature maps were obtained without converting the sound data into images. The MFCC method is a method that extracts feature from sound signals and is frequently used in the literature. Thanks to this method, it is possible to work directly on sound signals. The MFCC method used in this study to diagnose snoring sounds was first used by Davis and Mermelstein in 1980 [27]. The MFCC method uses the Hamming window technique to shape the sound signal and divide it into smaller windows. Spectrum is produced for each frame using the Fast Fourier transform and the filter bank is weighted. Finally, the MFCC vector is obtained by using the Logarithm and Discrete Cosine transformations. Filter banks are obtained using equation 1.

$$H_m(k) = \begin{cases} 0 & k < f(m-1) \\ \dfrac{k - f(m-1)}{f(m) - f(m-1)} & f(m-1) \le k \le f(m) \\ \dfrac{f(m+1) - k}{f(m+1) - f(m)} & f(m) \le k \le f(m+1) \\ 0 & k > f(m+1) \end{cases} \quad \text{(Eq.1.)}$$

In Equation 1, M represents the desired number of filters and f shows the list of frequencies. The MFCC method is a method that is frequently used especially in biomedical studies [28, 29]. The block diagram of the MFCC method is given in Figure 4.

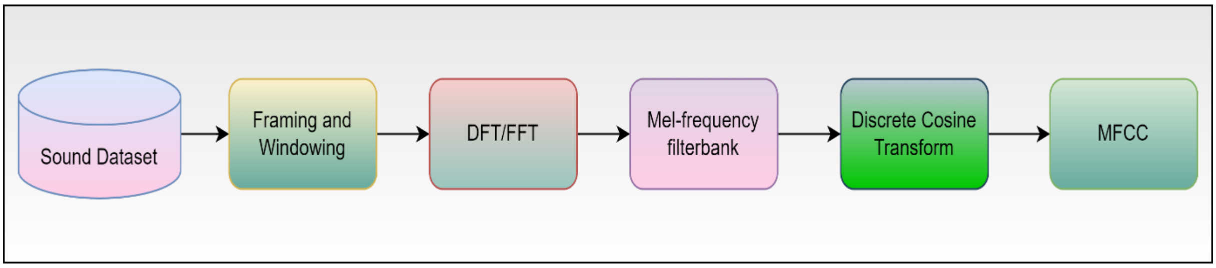

Figure 4. The block diagram of the MFCC method

The feature map obtained using the MFCC method was classified in 6 different supervised classifiers. Classifiers known in the literature were used in the study. These classifiers are Naïve Bayes [30], Support Vector Machine (SVM) [31], Logistic Regression [32], k-nearest neighborhood (KNN) [33], Gradient Boosting [34], and Random Forest [35].

2.4. Proposed Model

In the proposed model, first of all, sound signals were converted into images by the Mel-spectrogram method. The feature maps of the images in the acquired spectrogram data set were obtained using the Alexnet and Resnet101 architectures. These architectures extract feature maps with different features from the same data set. Therefore, these two architectures are used as the basis in the proposed hybrid model. The feature maps obtained using the Alexnet and Resnet101 architectures were combined. In this way, different features of the same image are brought side by side. NCA size reduction method was used to optimize the features in this feature map. In this way, the new size of the 1000x2000 feature map has become 1000x500. This allows the developed model to be trained in a shorter time. Finally, the optimized feature map is classified in the Bilayered Neural Network. Figure 5 depicts the suggested model's block diagram.

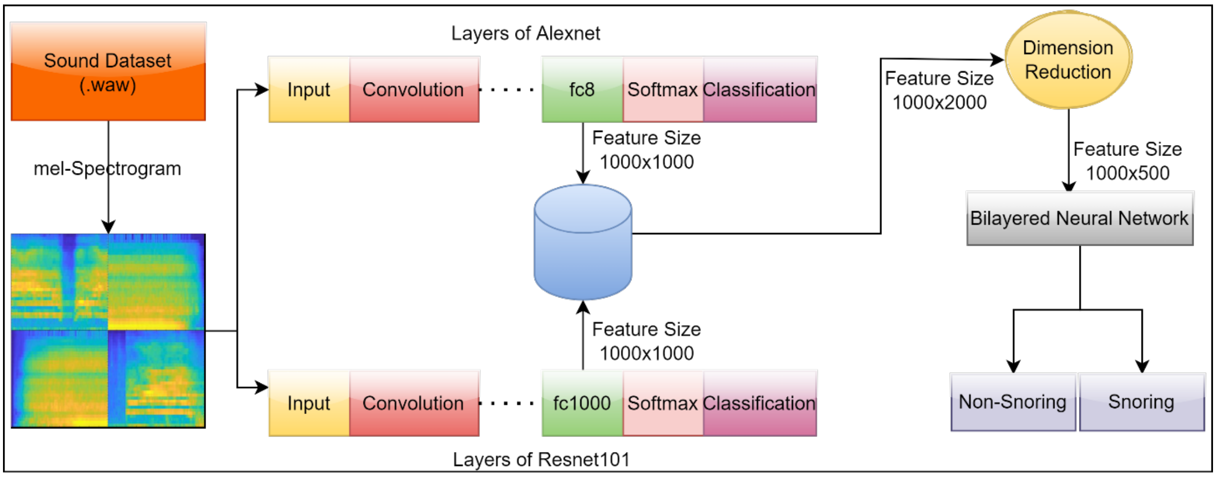

Figure 5. The suggested model's block diagram

Looking at Figure 5, the feature maps of the data set were obtained from the "fc8" layer of the Alexnet architecture, while it was obtained from the "fc1000" layer of the Resnet101 architecture. While the number of features obtained in both architectures was 1000, this number increased to 2000 after the merge process. After NCA size reduction, this number has decreased to 500 and has been classified in the Bilayered Neural Network.

3.Application Results

Matlab and Python environments were used in the implementation. Two different methods were used to diagnose snoring sounds. In the first method, sound signals were converted into images using the Mel-spectrogram method. Then, the obtained spectrogram images were first classified into 8 different classifiers and the proposed hybrid model. In the second method used in the study, feature maps were extracted using the MFCC method. The feature maps produced in the MFCC method were classified into 8 different classifiers. Confusion matrices are presented in detail in the study in order to compare the results obtained in different models and the proposed hybrid model using different methods [36].

3.1. Results obtained in deep models

In this study, first of all, sound signals were converted into images by using the Mel-spectrogram method. Obtained spectrogram images were classified using 8 different deep models accepted in the literature. 80% of the data in the data set was used in the training process of the models, and 20% in the testing phase of the models. Table 1 shows the accuracy rates obtained in deep models.

Table 1. Accuracy rates in state-of-the-art models

Alexnet	**Darknet53**	**Resnet101**	**Densenet201**
90%	89%	89%	88.5%
Googlenet	**MobilenetV2**	**InceptionV3**	**Efficientnetb0**
88%	88%	88%	87%

When the accuracy values obtained in Table 1 are examined, the accuracy rate obtained in Alexnet architecture is 90%, while 89% accuracy in Darknet53 and Resnet101 architecture, 88.5% in Densenet201 architecture, 88% in Googlenet, MobilenetV2, and InceptionV3 architectures and 87% in Efficientnetb0 architecture. In classifying spectrogram images, the most successful deep model was Alexnet with 90% accuracy, while the most unsuccessful deep model was Efficientnetb0 with 87% accuracy. Confusion matrices obtained using deep models are given in Figure 6.

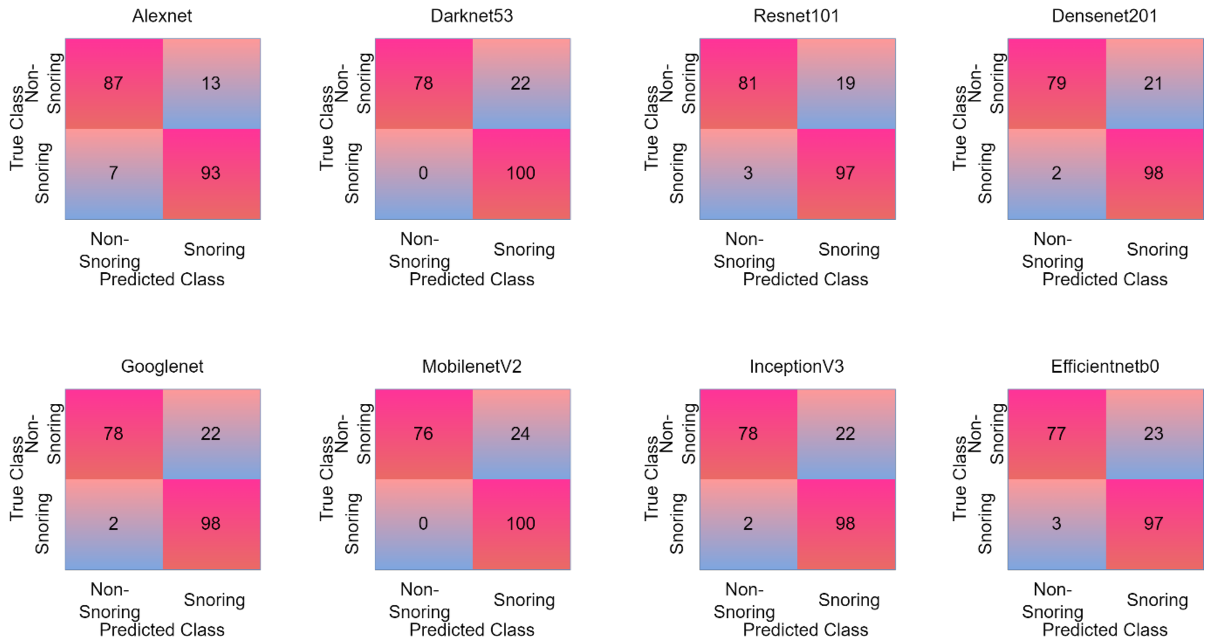

Figure 6. Confusion matrix in state-of-the-art models

In Figure 6, it is seen that Alexnet architecture makes the most successful classification. While the Alexnet architecture correctly predicted 180 of 200 test data, it predicted 20 test data incorrectly. While there is a balance in the number of data that the Alexnet architecture predicts incorrectly, the rate of predicting the data belonging to the Snore class as if it belongs to the Normal class is much higher in other architectures. Among the 8 models used in the study, the model that made the most incorrect predictions were the Efficientnetb0 model. While this model predicted 174 of 200 test data correctly, it predicted 26 of them incorrectly. If deep models are to be used to detect snoring sounds, it would be more appropriate to use Alexnet architecture.

3.2. Classification of feature maps obtained by MFCC method in classifiers

The second method used to diagnose snoring sounds is the MFCC method. With the MFCC method, the feature map of the sound signals was obtained and classified in different classifiers. The obtained accuracy values are presented in Table 2.

Table 2. MFCC + Classifiers

Naive Bayes	SVM	Logistic Regression
82.5%	87.5%	89%
KNN	**Gradient Boosting**	**Random Forest**
96%	96%	**98%**

The feature map produced in the MFCC method was classified in 6 different supervised classifiers. The Random Forest classifier achieved the greatest accuracy of 98% among these classifiers. The Naive Bayes classifier had the lowest accuracy rating of 82.5%. Confusion matrices obtained in supervised classifiers are given in Figure 7.

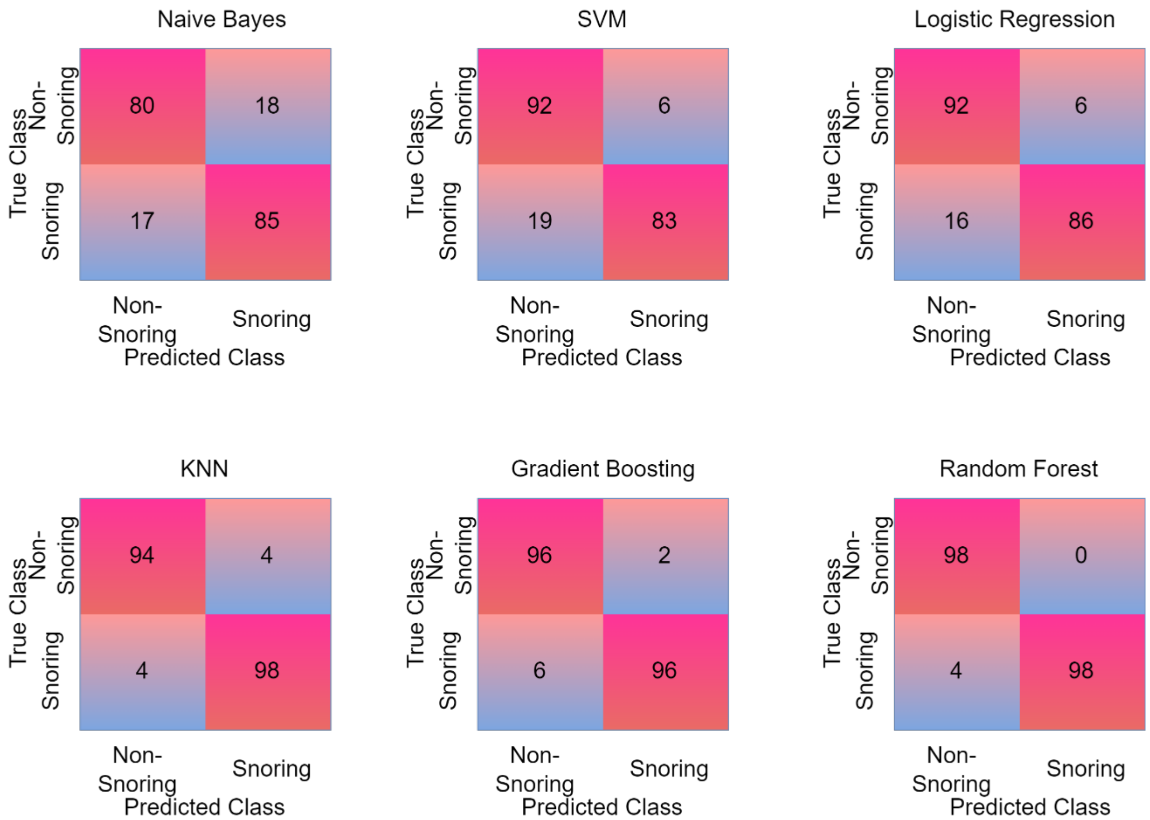

Figure 7. MFCC + Classifiers

The Random Forest classifier is clearly the most successful, as shown in Figure 7. Random Forest classifier predicted 196 out of 200 test data correctly and predicted 4 test data incorrectly. The data that the Random Forest classifier predicted incorrectly belonged to the Snoring class and was predicted as non-snoring by the model. The model with the most incorrect predictions was Naive Bayes. Naive Bayes guessed correctly 165 of 200 test images and mispredicted 35 of them.

3.3. Proposed Model

A hybrid model is proposed for diagnosing snoring sounds with a high success rate. Alexnet and Resnet101 architectures were utilized as the foundation for the proposed hybrid model, and feature maps of the data in the data set were obtained. Since the feature maps of each architecture are different from each other, different features were obtained from the same data set. After the obtained feature maps were combined, unnecessary features were eliminated using the NCA method. Finally, the optimized feature map is classified in the Bilayered Neural Network. The confusion matrix obtained in the proposed method is shown in Figure 8.

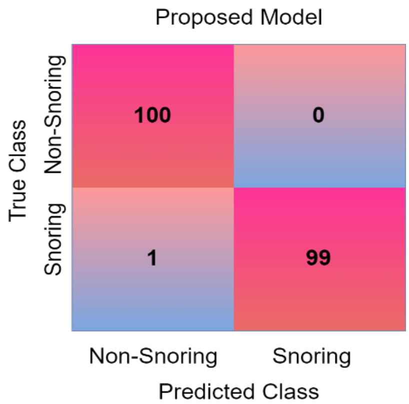

Figure 8. Confusion matrix of the proposed method

Figure 8 shows that the suggested model correctly identifies 199 of the 200 test data while wrongly classifying one. While the data that the proposed model misclassified belonged to the snoring class, the proposed model incorrectly predicted this data as non-snoring. The performance metrics of the proposed model are given in Table 3.

Table 3. Performance measurement parameters of the proposed model

Accuracy%	**Sensitivity%**	**Specificity%**	**False Positive Rate%**	**False Discovery Rate%**
99.50	99.01	100	0	0
False Negative Rate%	**Negative Predictive Value%**	**Precision%**	**F1 Score%**	**Matthews Correlation Coefficient%**
0.99	99	100	99.50	99

It is observed that the model proposed in Table 3 has achieved high success in classifying snoring sounds. the proposed model, it is seen that a 99.5% Accuracy value, 99.01% Sensitivity value, and 100% Specificity value are obtained in the process of diagnosing snoring sounds. ROC curves obtained in the proposed model are given in Figure 9.

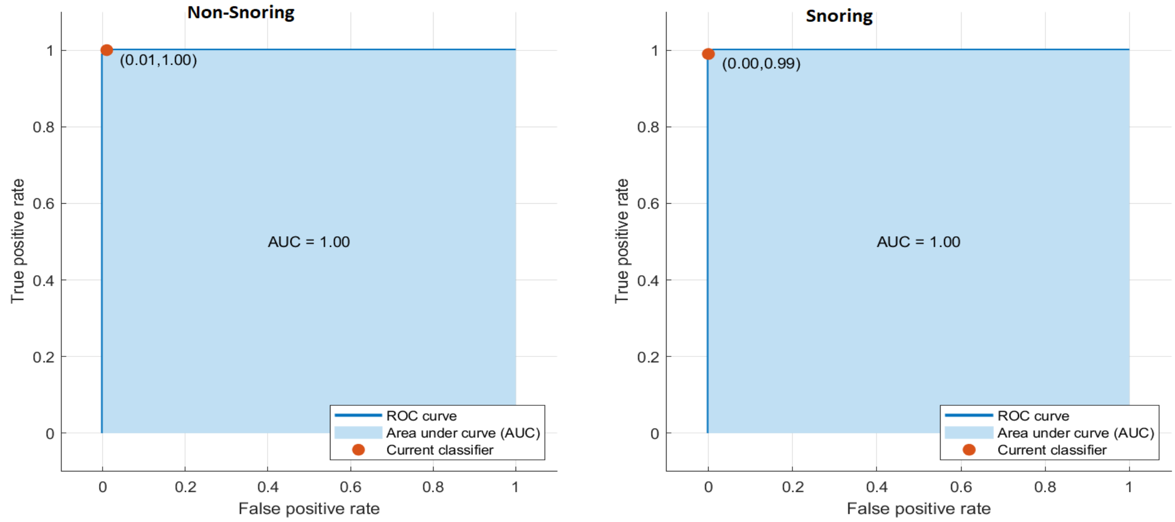

Figure 9. ROC Curves of Proposed model

When the ROC curves shown in Figure 9 are observed, the success of the proposed method in diagnosing snoring sounds can be observed.

4. Discussion

Snoring is a common sleep problem in humans. This problem has a negative effect on the sleep pattern of the person and their partner. Snoring can cause various diseases when left untreated. Because the amount of oxygen in the blood may decrease during snoring. Heart diseases, fatigue, diabetes, stroke, and psychological problems are some of the disorders that can be caused by snoring [37, 38]. Since snoring is a problem that can be treated, it will be faster and easier to detect this ailment thanks to computer-aided systems. In this study, a hybrid model was developed to diagnose snoring sounds. In the developed model, feature extraction was done with two different deep models and these feature maps were combined. In this way, different features of the sound signals in the data set are brought together. In order to make the proposed model work faster, the size reduction process was performed. NCA method was preferred for this process. The proposed hybrid model is compared with similar studies performed for the classification of snoring sounds in Table 4.

Table 4. Studies for the diagnosis of snoring sounds

Study	Classes	Method	Accuracy
Khan et al. [7]	Snoring, Non-snoring	Proposed CNN based model	96%
Jiang et al. [8]	Snoring, Non-snoring	LSTM, DNN, CNN, Mel-spectrogram	95.07%
Cavusoglu et al. [9]	Snoring, Non-snoring	Sub-band spectral energy	90.2%
Dafna et al. [10]	Snoring,	MFCC, LPC, Adaboost	98.2%

	Non-snoring		
Wang et al. [11]	Snoring, Non-snoring	Linear and non-linear feature extraction methods, SVM	94.5%
Lim et al. [12]	Snoring, Non-snoring	STFT, MFCC	98.9%
Arsenali et al. [13]	Snoring, Non-snoring	MFCC, Recurrent Neural Network	95%
Shen et al. [14]	Snoring, Non-snoring	MFCC, LPMFCC,LPC, CNN,LSTM	87%
Proposed Model	Snoring, Non-snoring	Spectrogram, deep models, NCA, Bilayered Neural Network	**99.5%**

It is seen in Table 4 that the proposed model has reached the highest accuracy value. In the proposed model, no metaheuristic optimization algorithm or a genetic algorithm type method is preferred to increase the performance rate. Feature selection was performed automatically with the NCA method. In addition, in the proposed hybrid model, deep models are only used for feature extraction. No time was spent training these models. At the same time, results were obtained by using 8 different deep models in the study. Among these results, Alexnet architecture obtained the highest accuracy rate with 90% accuracy. The proposed model has been more successful than these models.

The proposed model has many advantages as well as some disadvantages. The main limitations are the small number of data used in the study and the inability to collect data from patients from different regions. One of our goals is to collect data with the help of more experts from different centers and to design a model that can serve over the internet. In addition, it is among our aims to apply the developed model to other sound data sets.

5. Conclusion

Snoring sounds are a serious problem that can disrupt the sleep patterns of people and others around them. If this problem is not treated, it can cause other diseases. Recording snoring sounds by experts is both time-consuming and costly. This study, it is aimed to automatically diagnose snoring sounds with the hybrid model proposed. In the proposed model, Alexnet and Resnet101 architectures are used for feature extraction. Since no training process is performed with these architectures in the proposed hybrid model, the proposed model is much faster than the CNN models. In addition, the feature map has been optimized by using the NCA dimension reduction method so that the proposed model can be trained in a faster time. A high accuracy value of 99.5% was obtained in the proposed hybrid model.

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Conflict of Interest

The authors declare no conflict of interest.

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References

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[1] Veiga, A., et al. An IoT-based smart pillow for sleep quality monitoring in AAL environments. in 2018 Third International Conference on Fog and Mobile Edge Computing (FMEC). 2018. IEEE.
[2] Oksenberg, A. and D.S. Silverberg, The effect of body posture on sleep-related breathing disorders: facts and therapeutic implications. Sleep medicine reviews, 1998. 2(3): p. 139-162.
[3] Kwekkeboom, K.L., et al., The role of inflammation in the pain, fatigue, and sleep disturbance symptom cluster in advanced cancer. Journal of pain and symptom management, 2018. 55(5): p. 1286-1295.
[4] https://www.everydayhealth.com/news/eleven-health-risks-snoring/.
[5] Jodaki, K., et al., Effect of rosa damascene aromatherapy on anxiety and sleep quality in cardiac patients: A randomized controlled trial. Complementary Therapies in Clinical Practice, 2021. 42: p. 101299.
[6] Tietjens, J.R., et al., Obstructive sleep apnea in cardiovascular disease: a review of the literature and proposed multidisciplinary clinical management strategy. Journal of the American Heart Association, 2019. 8(1): p. e010440.
[7] Khan, T., A deep learning model for snoring detection and vibration notification using a smart wearable gadget. Electronics, 2019. 8(9): p. 987.
[8] Jiang, Y., J. Peng, and X. Zhang, Automatic snoring sounds detection from sleep sounds based on deep learning. Physical and engineering sciences in medicine, 2020. 43(2): p. 679-689.
[9] Cavusoglu, M., et al., An efficient method for snore/nonsnore classification of sleep sounds. Physiological measurement, 2007. 28(8): p. 841.
[10] Dafna, E., A. Tarasiuk, and Y. Zigel, Automatic detection of whole night snoring events using non-contact microphone. PloS one, 2013. 8(12): p. e84139.
[11] Wang, C., et al., Automatic snoring sounds detection from sleep sounds via multi-features analysis. Australasian physical & engineering sciences in medicine, 2017. 40(1): p. 127-135.
[12] Lim, S.J., et al., Classification of snoring sound based on a recurrent neural network. Expert Systems with Applications, 2019. 123: p. 237-245.
[13] Arsenali, B., et al. Recurrent neural network for classification of snoring and non-snoring sound events. in 2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). 2018. IEEE.
[14] Shen, F., et al., Detection of Snore from OSAHS Patients Based on Deep Learning. Journal of Healthcare Engineering, 2020. 2020.
[15] Skoczylas, A., et al., Belt conveyors rollers diagnostics based on acoustic signal collected using autonomous legged inspection robot. Applied Sciences, 2021. 11(5): p. 2299.
[16] Bhatti, F.A., et al., Shared spectrum monitoring using deep learning. IEEE Transactions on Cognitive Communications and Networking, 2021. 7(4): p. 1171-1185.
[17] Krizhevsky, A., I. Sutskever, and G.E. Hinton, Imagenet classification with deep convolutional neural networks. Advances in neural information processing systems, 2012. 25.
[18] Redmon, J. and A. Farhadi, Yolov3: An incremental improvement. arXiv preprint arXiv:1804.02767, 2018.
[19] He, K., et al. Deep residual learning for image recognition. in Proceedings of the IEEE conference on computer vision and pattern recognition. 2016.
[20] Huang, G., et al. Densely connected convolutional networks. in Proceedings of the IEEE conference on computer vision and pattern recognition. 2017.
[21] Szegedy, C., et al. Going deeper with convolutions. in Proceedings of the IEEE conference on computer vision and pattern recognition. 2015.
[22] Howard, A.G., et al., Mobilenets: Efficient convolutional neural networks for mobile vision applications. arXiv preprint arXiv:1704.04861, 2017.
[23] Szegedy, C., et al. Rethinking the inception architecture for computer vision. in Proceedings of the IEEE conference on computer vision and pattern recognition. 2016.
[24] Tan, M. and Q. Le. Efficientnet: Rethinking model scaling for convolutional neural networks. in International conference on machine learning. 2019. PMLR.
[25] Eroğlu, O. and M. Yildirim, Automatic detection of eardrum otoendoscopic images in patients with otitis media using hybrid-based deep models. International Journal of Imaging Systems and Technology, 2022. 32(3): p. 717-727.
[26] Bingol, H. (2022). NCA-based hybrid convolutional neural network model for classification of cervical cancer on gauss-enhanced pap-smear images. International Journal of Imaging Systems and Technology.
[27] Davis, S. and P. Mermelstein, Comparison of parametric representations for monosyllabic word recognition in continuously spoken sentences. IEEE transactions on acoustics, speech, and signal processing, 1980. 28(4): p. 357-366.
[28] Deng, M., et al., Heart sound classification based on improved MFCC features and convolutional recurrent neural networks. Neural Networks, 2020. 130: p. 22-32.
[29] Karan, B., S.S. Sahu, and K. Mahto, Parkinson disease prediction using intrinsic mode function based features from speech signal. Biocybernetics and Biomedical Engineering, 2020. 40(1): p. 249-264.

[30] Rish, I. An empirical study of the naive Bayes classifier. in IJCAI 2001 workshop on empirical methods in artificial intelligence. 2001.
[31] Joachims, T., 11 Making Large-Scale Support Vector Machine Learning Practical. Advances in kernel methods: support vector learning, 1999: p. 169.
[32] Kleinbaum, D.G., et al., Logistic regression. 2002: Springer.
[33] Keller, J.M., M.R. Gray, and J.A. Givens, A fuzzy k-nearest neighbor algorithm. IEEE transactions on systems, man, and cybernetics, 1985(4): p. 580-585.
[34] Friedman, J.H., Greedy function approximation: a gradient boosting machine. Annals of statistics, 2001: p. 1189-1232.
[35] Liaw, A. and M. Wiener, Classification and regression by randomForest. R news, 2002. 2(3): p. 18-22.
[36] Eroglu, Y., et al., Diagnosis and grading of vesicoureteral reflux on voiding cystourethrography images in children using a deep hybrid model. Computer Methods and Programs in Biomedicine, 2021. 210: p. 106369.
[37] Brockmann, P.E., et al., Reduced sleep spindle activity in children with primary snoring. Sleep Medicine, 2020. 65: p. 142-146.
[38] Macarthur, K.E., et al., Dissociation between objectively quantified snoring and sleep quality. American Journal of Otolaryngology, 2020. 41(1): p. 102283.