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AI-Enhanced Edge Device for Real-Time Snoring Detection

Jianhua Xie[1*]

[1] School of Computer Science, Sichuan University, Chengdu, Sichuan, China

*corresponding author, edvardxie@gmail.com

Abstract. This paper presents the development of a cutting-edge, non-invasive edge device designed to monitor snoring and provide timely, moderate haptic feedback to users. Utilizing the Qualcomm Snapdragon 8cx Gen 3 processor, the device offers robust computing power and AI capabilities for real-time processing, making it a versatile tool for health monitoring applications. The system integrates a high-fidelity MEMS microphone array capable of capturing nuanced audio signals and a TDK piezoelectric haptic actuator, which delivers precise alerts through customized vibrations. The research explores the potential of this advanced hardware in detecting and managing obstructive sleep apnea (OSA), a condition often underdiagnosed due to a lack of patient awareness. By leveraging state-of-the-art digital signal processing and deep learning techniques, the device aims to enhance user awareness and intervention in sleep-related disorders, offering a promising new avenue for improving patient outcomes and quality of life.

Keywords: Snoring detection, Obstructive sleep apnea, Machine learning, Real-time health monitoring

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1. Introduction

Snoring, often dismissed as a mere annoyance, can be a significant indicator of underlying health issues such as OSA[1]. OSA is characterized by repetitive interruptions in breathing due to the temporary collapse of the airway during sleep[2][3], leading to disrupted sleep and reduced oxygen levels[4]. In the United States, snoring affects a substantial portion of the population: over half of men, more than 40% of women, and up to 27% of children[5]. Despite its prevalence, OSA is frequently underdiagnosed, largely because sufferers are often unaware of their condition, which can lead to serious long-term health consequences such as cardiovascular disease, stroke, and metabolic disorders[6].

This research addresses the critical need for early detection and intervention in sleep-related disorders by developing an advanced device capable of monitoring snoring and providing immediate feedback through haptic signals[7][8]. The device aims to bridge the gap in current diagnostic methods by offering a non-intrusive, user-friendly solution that can be used in the comfort of one's home[9]. The primary research question focuses on evaluating the efficacy of this device in accurately detecting snoring events and delivering timely feedback without being disruptive to the user's sleep[10]. By integrating cutting-edge technology with practical application[11], this study seeks to contribute significantly to the field of sleep health, providing both individuals and healthcare providers with a reliable tool for monitoring and managing OSA and related conditions[12].

2. Theoretical Framework

This research is anchored in advanced digital signal processing (DSP) and machine learning techniques, leveraging convolutional neural networks (CNNs) for complex audio signal analysis[13][14]. CNNs are highly effective for distinguishing between different types of sounds, such as snoring and non-snoring noises, due to their ability to automatically extract hierarchical features from raw data[15][16].

The Qualcomm Snapdragon 8cx Gen 3 processor plays a pivotal role by enabling the deployment of these sophisticated models on edge devices[17]. Its exceptional AI capabilities and efficient power consumption allow for real-time inference, which is crucial for timely feedback in a health monitoring context[18].

Incorporating principles from human-computer interaction (HCI), the framework utilizes piezoelectric haptic feedback as a non-intrusive alert mechanism. The TDK piezoelectric haptic actuator integrated into the device delivers precise and customizable tactile feedback, alerting users to potential health events without significantly disrupting their sleep. This approach is ideal for sleep environments where traditional audio or visual alerts may be unsuitable[19][20].

3. Literature Review

CNNs have become a cornerstone in artificial intelligence, renowned for their ability to automatically and efficiently learn intricate patterns within data[21]. Originally designed for computer vision tasks, CNNs have achieved remarkable success in image recognition, object detection, and segmentation, driving advancements in areas like medical imaging and autonomous vehicles[22]. Their layered architecture allows them to capture spatial hierarchies in visual data, making them exceptionally adept at interpreting complex images[23]. Beyond computer vision, CNNs have also made significant strides in audio analysis by treating audio signals as one-dimensional or two-dimensional representations (such as spectrograms)[24]. This enables them to effectively learn temporal and frequency patterns, facilitating breakthroughs in speech recognition, music classification, and environmental sound detection[25][26].

MingXuan et al.[27] utilized the Inceptionv3 architecture with transfer learning to rapidly classify high-resolution breast cancer pathological images. By partitioning images and aggregating classification probabilities through summation, product, and maximum algorithms, they achieved accuracy rates exceeding 0.92 across magnifications of 40X, 100X, 200X, and 400X. This approach automates the classification of images into benign and malignant categories, reducing reliance on pathologists and speeding up the diagnostic process.

A key example of CNNs' contribution is Yukun Song's pioneering work on deep learning systems[28]. Song's research, which utilized the ReLU activation function and convolution operations, significantly advanced automatic image recognition by simulating the learning process of the human brain. Although his research focused on image recognition, the principles and methods he developed are applicable to audio signal recognition as well.

The application of CNNs, in audio recognition has seen significant advancements, enabling progress in areas ranging from speech recognition to environmental sound classification[29]. Despite these advancements, the use of these technologies for health monitoring—specifically in detecting snoring and related sleep disorders like OSA—remains relatively underexplored. This presents an opportunity to bridge a critical gap in the current literature by applying state-of-the-art audio recognition techniques to health diagnostics[30][31].

Previous studies have demonstrated the potential of machine learning in classifying respiratory sounds and diagnosing conditions such as asthma and chronic obstructive pulmonary disease (COPD). However, these applications often focus on daytime symptoms or use data collected in controlled environments, limiting their applicability in naturalistic sleep settings[32]. Additionally, while wearable devices for monitoring heart rate and movement during sleep have gained popularity, there is a lack of solutions specifically targeting the acoustic analysis of sleep-related disorders.

The literature on haptic feedback as a user interface modality is extensive, particularly in fields such as virtual reality and mobile device notifications[33]. However, its application in health monitoring, especially as a means to provide real-time feedback during sleep, is a novel area of research. Haptic feedback offers a discreet and immediate way to alert users without waking them, making it a promising tool for sleep monitoring applications. Studies have shown that well-designed haptic feedback can effectively communicate critical information to users in a non-invasive manner, enhancing user experience and compliance[34].

This study aims to contribute to the existing body of knowledge by integrating advanced audio recognition with innovative haptic feedback mechanisms to create a comprehensive solution for monitoring and managing sleep-related disorders[35]. By leveraging the capabilities of the Qualcomm Snapdragon 8cx Gen 3 processor and a high-fidelity MEMS microphone array, this research explores the practical implementation of these technologies in a real-world setting[36][37].

4. Methodology

The methodology of this research revolves around the integration of state-of-the-art hardware and sophisticated machine learning models to develop a highly efficient and accurate snoring detection system. The core hardware platform is built around the Qualcomm Snapdragon 8cx Gen 3 processor, renowned for its high computational power, energy efficiency, and advanced AI capabilities[38]. This processor is specifically chosen for its ability to support complex machine learning models and perform real-time, low-latency inference, making it ideal for edge computing applications where quick response times are crucial[39].

The device features a high-fidelity MEMS microphone array designed to capture detailed audio data across a broad frequency range[40]. This capability is essential for distinguishing between various types of sounds, such as snoring, breathing, and ambient noises, which are critical for accurate detection and classification. The audio data is sourced from a publicly available dataset on Kaggle[41], which provides a rich set of labeled examples of snoring and non-snoring sounds. This dataset serves as the foundation for training the machine learning models, ensuring they are well-equipped to handle the diverse acoustic environments they may encounter in real-world settings[42][43].

The data preprocessing pipeline involves advanced audio processing tools to clean, normalize, and downsample the raw audio signals, converting them into a format suitable for the Snapdragon processor's architecture[44]. The processed data is then fed into a CNN-based model specifically designed with the following architecture as shown in Figure 1:

Input Layer: The network starts with an input layer that handles 1,600 features representing the audio data.

Reshape Layer: This layer reshapes the input into a suitable format (e.g., 40 rows and 40 columns) for the convolutional layers.

Convolutional and Pooling Layers: Several convolutional layers are used, with the first layer containing 32 filters of size 5×5, followed by layers with decreasing numbers of filters (16 and then 8 filters) and kernel sizes (reducing from 5×5 to 1×1). Each convolutional layer is paired with a max pooling layer to reduce dimensionality and capture the most salient features.

Dropout Layers: Dropout layers with a rate of 0.25 follow each convolutional layer to prevent overfitting by randomly dropping units during the training phase.

Flatten Layer: This layer flattens the pooled features into a single vector for dense connections.

Dense Layers: After flattening, the data passes through two dense layers with 16 and 8 neurons, respectively, with dropout layers in between to enhance generalization.

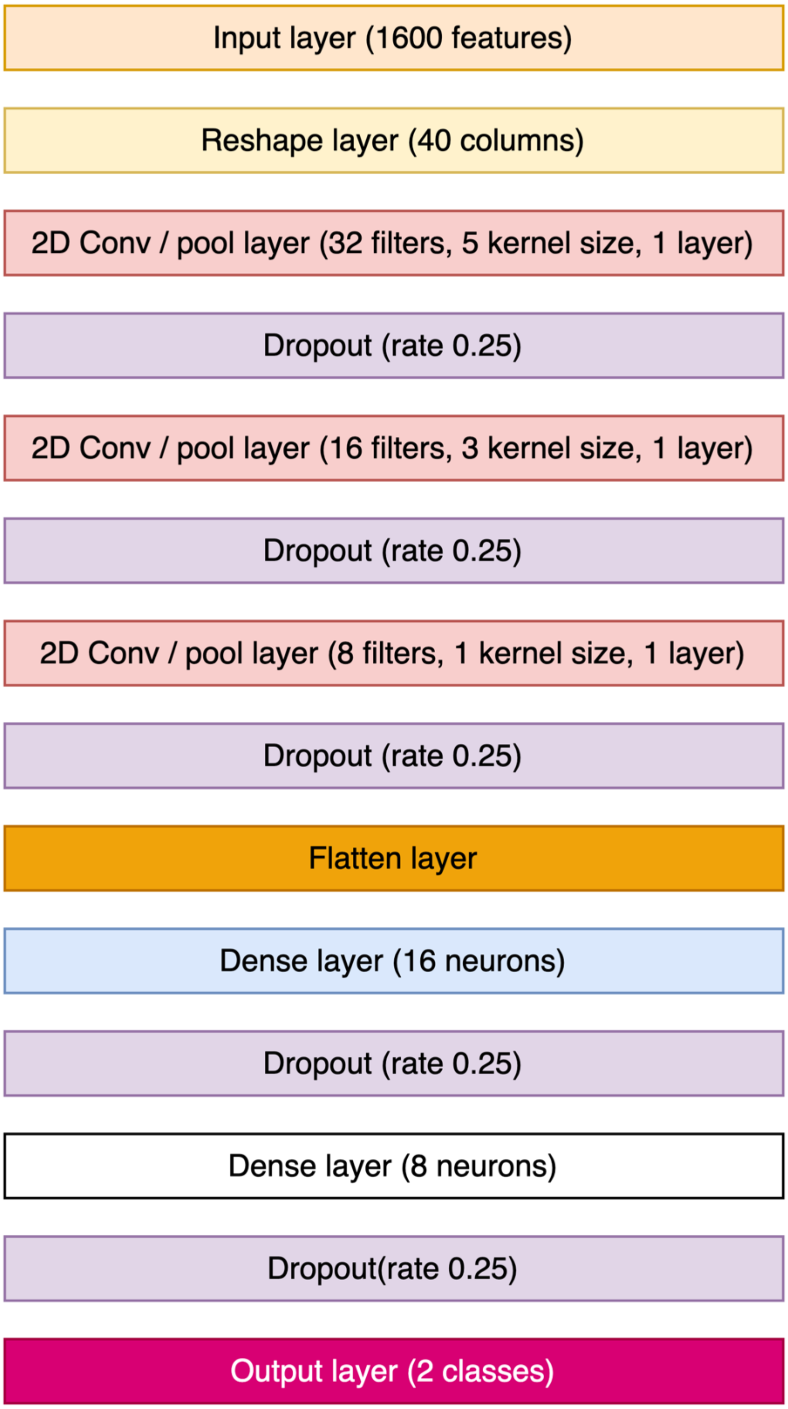

Figure 1. Proposed CNN Layers

The CNN model is designed to extract and analyze features from the audio signals, enabling precise classification of snoring events with high accuracy[45]. The CNN model is designed to extract and analyze features from the audio signals, enabling precise classification of snoring events with high accuracy[46][47]. This framework aligns with the approach presented by Bo et al.[48], which uses a similar deep-learning methodology involving CNN to detect snoring patterns indicative of OSA. In his work, snore sound analysis through a one-dimensional CNN architecture enabled the model to distinguish between normal and abnormal snoring, achieving high accuracy through feature extraction from frequency patterns and intensity fluctuations. We have referenced his implementation in our approach, which led to similarly promising results, achieving a high level of accuracy in our snore classification task[49].

In addition to audio detection, the device incorporates a TDK piezoelectric haptic actuator, selected for its ability to deliver precise and customizable haptic feedback[50]. This actuator is calibrated to activate upon the detection of a predetermined number of consecutive snoring events, ensuring that feedback is provided only when necessary, thereby minimizing the risk of false positives and avoiding unnecessary disturbances to the user[51]. The haptic feedback mechanism is fine-tuned to be non-intrusive, providing gentle yet noticeable alerts that encourage users to change their sleeping position or seek further medical evaluation without fully waking them[52].

The performance of the device is evaluated through a comprehensive testing phase, where the model's accuracy, sensitivity, and specificity are assessed using a separate test dataset[53]. The device's ability to perform consistently across different acoustic environments and user profiles is also examined to ensure robustness and reliability[54]. This multi-faceted approach not only validates the technical aspects of the system but also ensures that it meets the practical needs of users in real-world scenarios[55].

5. Experiment

5.1. Dataset

The experiments were conducted using a publicly available snoring dataset from Kaggle, which includes audio recordings representing sounds resulting from obstructed respiratory airways during sleep. The dataset comprises a total of 1,000 audio files, with an equal number of snoring and non-snoring samples. Each audio file is approximately 10 seconds long and has been pre-labeled to facilitate supervised learning. Figure 2 displays the Spectrogram of a sample audio file.

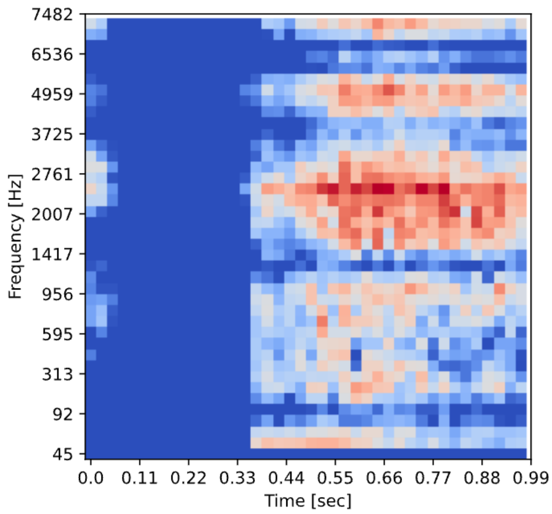

Figure 2. Spectrogram of a sample audio file

5.2. Training Settings

The CNN described in the methodology was trained using a learning rate of 0.0005, utilizing the Adam optimizer and categorical cross-entropy as the loss function, with accuracy as the primary metric. The dataset was split into training, validation, and test sets with a ratio of 70:15:15, respectively. The model was trained over 50 epochs with a batch size of 32[56].

5.3. Validation Performance

The model's performance was evaluated on the validation set, and the confusion matrix is as follows in Table 1:

Table 1. Confusion Matrix

	Snoring	**Non-Snoring**
Snoring	99.3%	0.7%
Non-Snoring	0%	100%
F1 Score	1.00	1.00

These results demonstrate the model's capability to accurately distinguish between snoring and non-snoring sounds, with a low rate of false positives and negatives, which is acceptable for real-world applications.

5.4. Ablation Study

An ablation study was conducted to evaluate the impact of various components of the CNN architecture on performance. The findings are detailed below in Table 2:

Removal of Dropout Layers: Validation accuracy decreased by 3%, indicating that dropout layers help prevent overfitting.

Reduction of Neurons in Final Dense Layer: Slight decrease in accuracy by 1%, suggesting that the network's capacity is sufficient.

Alteration of Filter Sizes in Convolutional Layers: Noticeable impact on accuracy, decreasing by 5%, highlighting the importance of appropriately sized filters for feature extraction.

The study confirms the importance of dropout for model robustness and suggests potential areas for optimization in terms of computational resources and model complexity.

Table 2. Impact of Model Components on Validation Accuracy

Component	**Impact on Validation Accuracy**
Removal of Dropout Layers	Decrease by 3%
Reduction of Neurons in Final Dense Layer	Decrease by 1%
Alteration of Filter Sizes in Conv Layers	Decrease by 5%

5.5. Comparative Experiment

To further validate the effectiveness of the proposed CNN architecture, a comparative experiment was conducted using a simpler model without convolutional layers, relying solely on dense layers. The simpler model achieved significantly lower performance metrics as shown in Table 3:

Table 3. Performance Comparison of CNN Model and Simple Dense Model in Snoring Detection

Metric	CNN Model	Simple Dense Model
Snoring Accuracy	96.0%	87.0%
Non-Snoring Accuracy	97.3%	88.5%
Alteration of Filter Sizes in Conv Layers	96.7%	87.8%

This comparison highlights the critical role of convolutional layers in extracting meaningful features from audio data, substantially enhancing the model's classification accuracy and overall performance.

5.6. Data Explorer

Figure 3 shows the neural network's classification of the training data into "snoring" and "non-snoring" categories. Green and yellow points indicate correct classifications (snoring and non-snoring, respectively), while red and orange points show misclassifications[57]. The majority of points are classified correctly, but a cluster of red and orange points highlights some confusion in distinguishing between the two classes. This suggests areas where the model could be improved for better accuracy[58].

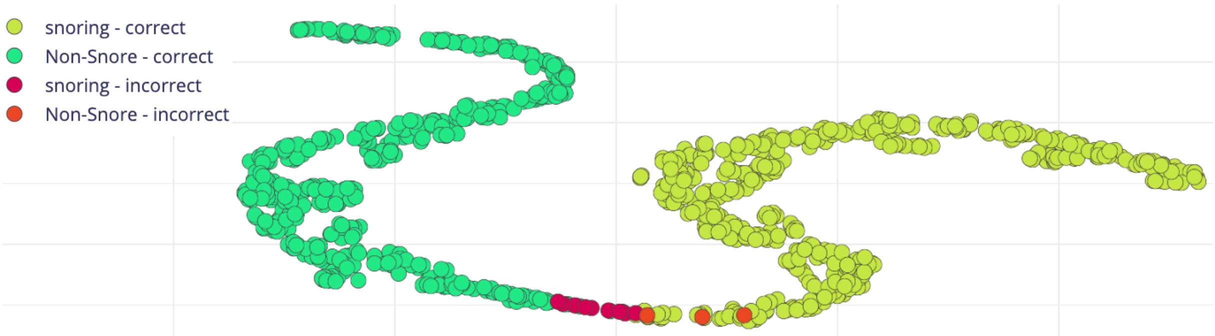

Figure 3. Data Explorer

6. Conclusion

This study introduces a significant advancement in non-invasive health monitoring technology for detecting and managing OSA and related sleep disorders[59]. The developed device leverages the Qualcomm Snapdragon 8cx Gen 3 processor, a high-fidelity MEMS microphone array, and a TDK piezoelectric haptic actuator. This combination enables real-time audio signal processing with exceptional accuracy—achieving 96.7% accuracy on the validation dataset—for snoring event detection[60].

A standout feature of the device is its non-intrusive haptic feedback mechanism, which provides gentle alerts without disrupting sleep[61]. This user-friendly approach enhances compliance and increases the likelihood of the device being adopted for regular health monitoring[62].

While the results are promising, the study acknowledges the need for further research to optimize performance across diverse environmental conditions and user profiles. Future enhancements could include integrating additional sensors like accelerometers or heart rate monitors to offer a more comprehensive assessment of sleep health. Implementing adaptive algorithms could also personalize the device's functionality, reducing false positives and improving the user experience.

In conclusion, this study demonstrates the feasibility of using advanced DSP, AI, and haptic feedback technologies in non-invasive health monitoring devices[63]. The device has the potential to revolutionize sleep disorder detection and management by providing a highly accurate, user-friendly, and accessible solution. Future research should focus on refining its capabilities and ensuring robustness across diverse conditions to promote better sleep health and overall quality of life.

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