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Implementation of Cough Detection System Using IoT Sensor in Respirator

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Abstract

Worldwide, the number of corona virus disease 2019 (COVID-19) confirmed cases is rapidly increasing. Although vaccines and treatments for COVID-19 are being developed, the disease is unlikely to disappear completely. By attaching a smart sensor to the respirator worn by medical staff, Internet of Things (IoT) technology and artificial intelligence (AI) technology can be used to automatically detect the medical staff's infection symptoms. In the case of medical staff showing symptoms of the disease, appropriate medical treatment can be provided to protect the staff from the greater risk. In this study, we design and develop a system that detects cough, a typical symptom of respiratory infectious diseases, by applying IoT technology and artificial technology to respiratory protection. Because the cough sound is distorted within the respirator, it is difficult to guarantee accuracy in the AI model learned from the general cough sound. Therefore, coughing and non-coughing sounds were recorded using a sensor attached to a respirator, and AI models were trained and performance evaluated with this data. Mel-spectrogram conversion method was used to efficiently classify sound data, and the developed cough recognition system had a sensitivity of 95.12% and a specificity of 100%, and an overall accuracy of 97.94%.

Keywords: *COVID-19, Smart Sensor, IoT, Non-Powered Hood Respirator, Mel-Spectrogram, Deep Learning, CNN*

1. Introduction

As of November 20, 2020, there were 56,623,643 confirmed cases of COVID-19 in 220 countries and territories worldwide, and 1,355,963 people died from the disease [1]. Many medical staff are making every effort to cope with this disease, but there are situations where medical resources are insufficient to cope with the rapidly increasing number of confirmed cases of the disease. Fortunately, 48 COVID-19 vaccines are being developed, of which 11 are in phase 3 clinical trials [1]. However, until the end of 2021, the impact of COVID-19 is expected to continue, and the disease is unlikely to disappear completely. Even if vaccines and treatments are developed, respirators must be worn for medical staff who care for patients. Respirators are classified into health masks for public health protection, surgical masks for surgeries by medical staff, ventilators for patients with difficulty in self-breathing, and industrial respirators for industrial workers. Personal protective

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equipment (PPE) that protects the body including the respiratory system is classified into Levels A, B, C, and D according to the standards set by the National Institute of Occupational Safety and Health (NIOSH) [2]. At the beginning of the outbreak of COVID-19, medical staff wore Level D-level health masks to treat COVID-19 patients, but recently, the use of Level A - Powered Air Purifying Respirator (PAPR) is gradually increasing [3]. Although the use of PAPR is desirable to deal with respiratory infectious diseases, there are several problems. Because PAPR is expensive and disposable, it is not suitable as an equipment to cope with the explosion of COVID-19 patients. In order to solve this problem, several projects are underway to develop a non-motorized hooded respirator using a snorkeling mask [4].

Among the difficulties experienced by medical personnel wearing respirators, fatigue and fear of infection are the greatest [5]. The fundamental solution to this is to secure enough medical staff and medical quarantine resources, but realistically, it is insufficient to cope with COVID-19. Respirators with smart sensors, IoT technology, and artificial intelligence technology can be used to automatically measure the fatigue of medical staff and signs of disease infection. Through this, it is possible to protect medical staff from a greater risk by taking appropriate treatment in the case of medical staff who have accumulated fatigue or who show signs of respiratory infectious diseases.

In this paper, we design and develop a system that detects cough, which is a representative symptom of respiratory infectious diseases, using a non-motorized hooded respirator equipped with a smart sensor, IoT technology, and artificial intelligence technology. The cough sound in the respirator is different from the cough sound that occurs in daily life. We collect coughing sounds and non-cough sounds in respirators, and use this data to train a convolutional neural network (CNN) model, one of the deep learning models. In addition, we demonstrate the usefulness of the cough recognition system in respirators by evaluating the performance of the model trained using the test data.

In Chapter 2, related works are reviewed. Chapter 3 explains the structure of the system for cough detection in IoT respirators, and describes how to extract sound sections that are candidates for cough from continuous sound streams. In addition, after converting the extracted sound section into Mel-spectrogram data, an AI model for cough recognition using this data as input is introduced. In Chapter 4, we implement a cough detection system, including an IoT respirator, and demonstrate its effectiveness by evaluating the performance of the AI model with a test set. Finally, Chapter 5 summarizes and concludes this paper.

2. Related Work

Several studies have been conducted on cough detection. A. Imran et al. [6] conducted a study to record the cough sound of a patient using a smartphone and to identify whether the recorded cough sound was a cough from COVID-19 disease using an AI engine running on a cloud server. In addition, they developed AI4COVID-19, an app that runs on smartphones, to evaluate the performance of this AI engine, and showed sufficient potential to confirm coughing of COVID-19. However, since the data used for training and testing of the AI model is small, the reliability of the performance evaluation is somewhat lower.

H. B. Carlos et al. [7] developed a system that efficiently detects cough while minimizing power consumption in a smartphone. Their system achieved a sensitivity of 88.94% and a specificity of 98.64% in the presence of noise.

M. You et al. [8] used a method of finding sub-band features using a gamma-tone filter bank and an audio feature extraction method to recognize cough. Cough sounds were detected by training Support Vector Machine (SVM), K-Nearest Neighbors (KNN) and Random Forest (RF) models using the found sub-band features. It has been shown that combining multiple frequency sub-bands improves cough detection performance.

G. Rudraraju et al. [9] proposed a method to identify respiratory diseases by analyzing cough sounds. They built a machine learning model to predict obstructive and restrictive patterns of air flow, and verified the performance using K-fold cross-validation technique based on actual data. The accuracy of pattern prediction was 91.97%, the sensitivity was 87.2%, and the specificity was 93.69%.

These existing studies aim to detect and analyze cough sounds in an open environment. In order to check the condition of the medical staff wearing respirators and recognize the cough sound, the AI model must be trained using the cough sound in the respirator. The sound of coughing in respirators differs from coughing in an open environment. In the respirator, it is less disturbed by external noise, while distortion of the sound occurs. In this study, we collect cough sounds and non-cough sounds in respirators, and design an AI model that recognizes cough in respirators. Also, we shows its usefulness by evaluating the performance of the developed system.

3. System Structure and Design

The overall structure of the system developed in this study is as shown in Figure 1. The sensor attached to the respirator records the wearer's sound and transmits it to the smartphone app through the communication module. The smartphone app retransmits the sound data received from the IoT respirator to the data server, and the data server inputs the transmitted sound data into the trained AI model to detect cough. If the wearer of the respirator coughs more than a certain number of times for a specified period of time, this should be notified to the manager of the medical staff so that the wearer's health can be managed.

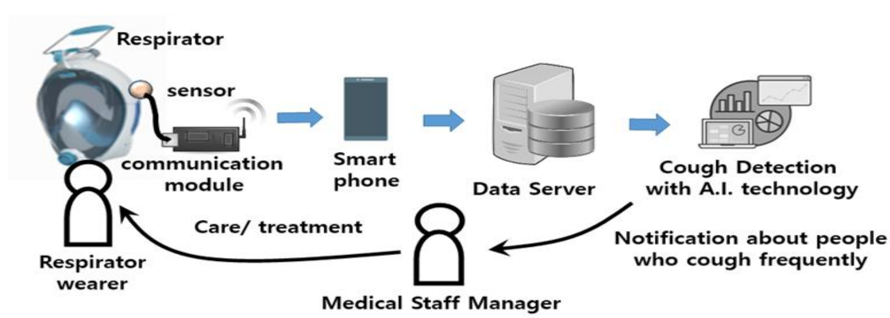

Figure 1. The overall structure of the cough detection system

3.1 Respirator with Smart Sensor

We used a non-motorized hooded respirator developed by a startup company, and the INMP441, an omnidirectional MEMS microphone developed by InvenSense, was used as a sensor for recording sound. As a communication module, the Bluetooth function of ESP32 developed by Espressif Systems was used. Figure 2 shows the respirator and IoT devices used in the development. Since the INMP441 and ESP32 devices operate at low power, they can operate for a long time with a small capacity battery. The ESP32 control program was developed using the Arduino IDE. This control program records sound from INMP441, packetizes the recorded sound data, and transmits it to a smartphone app linked with Bluetooth. In the smartphone app, the transmitted sound data is accumulated for a certain period of time and then retransmitted to the data server.

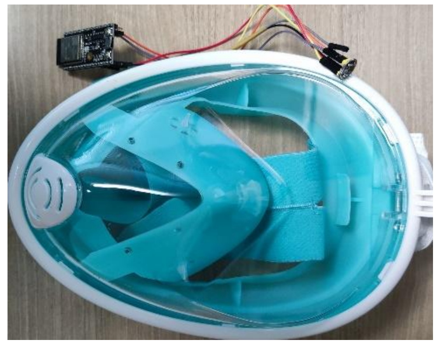

Figure 2. Respirator and IoT devices

3.2 Extraction of cough sound frames

In order to detect cough in a continuous audio stream, first, sound data must be separated into frames of a certain size. As shown in the waveform of the cough sound in Figure 3, in the case of coughing, a strong sound occurs from the beginning, and the duration of the cough sound is in most cases within 0.3 seconds. Therefore, our programs analyze the sound frame in units of 10msec, and if a frame with the loudness exceeding a certain threshold is found, the 300msec sound section starting from the frame is cut and saved as a wav-format file.

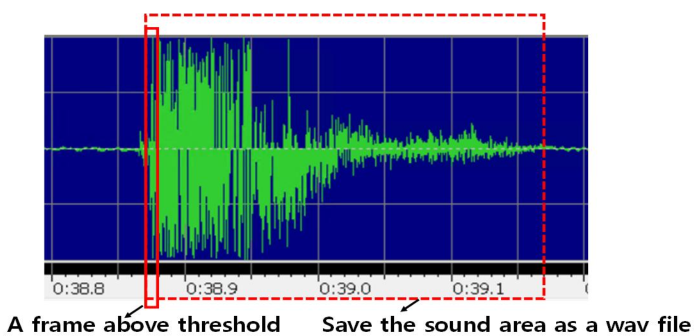

Figure 3. Separation of cough area from sound data

3.3 Conversion of sound data to Mel-spectrogram

The wav-format file stored in the form of the loudness over time is not efficient to use as an input of a deep learning model. In a number of existing studies, the Mel-spectrogram transformation method was used to efficiently classify sound data [10-11].

In this study, we also use a Mel-spectrogram that expresses the characteristics of speech well according to the way people perceive sound by frequency band. That is, the wav-format file extracted in the previous step is converted into Mel-spectrogram data and used as the input of the deep learning model. Figure 4 shows the data obtained by converting the cough sound waveform into a Mel-spectrogram as an image.

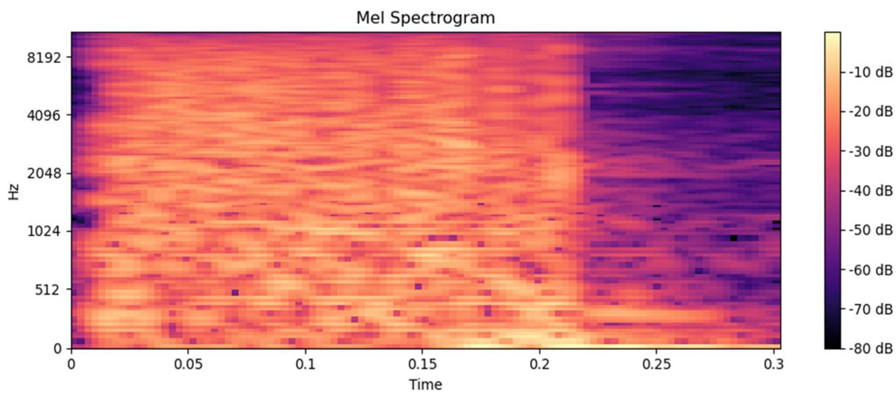

Figure 4. Example of Mel-spectrogram image of coughing sound

3.4 AI model for cough detection

We used the CNN model as the AI model, and implemented the CNN model using TensorFlow and Keras. Figure 5 shows the internal structure of the AI model designed in this study. After converting the sound data into Mel-spectrogram data, the converted data is used as an input to the CNN model.

Mel-spectrogram is regarded as an image with a size of 128x300, and this input data is connected to 512 nodes through 3 convolution operations and 3 max-pooling operations. The final output of this model is 0 (not cough) or 1 (cough).

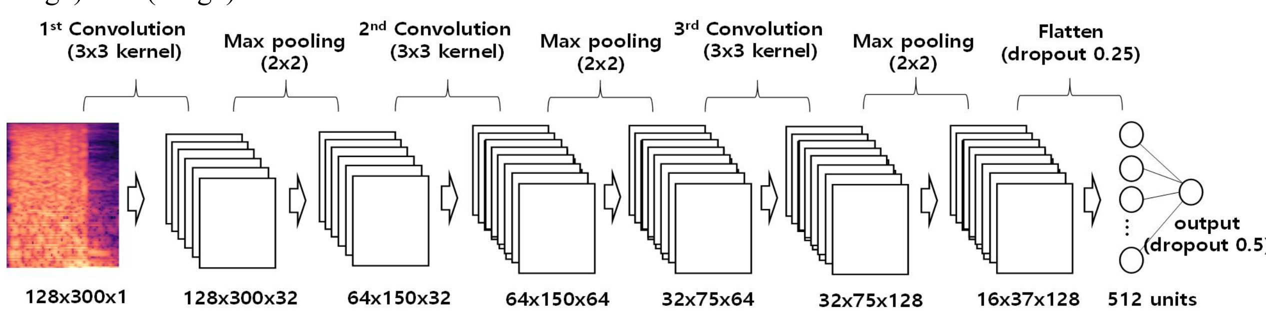

Figure 5. CNN model configuration for cough detection

4. System Implementation and Performance Evaluation

The development environment used to implement the cough detection system in IoT respirator is as follows.

- Hardware
  - Non-motorized hooded respirator
  - Microphone sensor : INMP441 developed by InvenSense
  - Communication module : ESP32 developed by Espressif Systems
  - PC Server : Intel I7 (3.6GHz, 4 cores), Nvidia GeForce GTX 960 (CUDA Core # 1024, 1164MHz)
- Software
  - Arduino IDE : Development environment for ESP32 device control program development
  - Android Studio 4.1.1 (with flutter and dart) : Development environment for Android apps
  - PyCharm 2020.2 (with tensorflow and keras) : Development environment for AI model implementation and training

All sound data were recorded by the sensor of the IoT respirator, and there were 256 cough sounds and 387 non-cough sounds. 85% of this data was used for training AI models, and 15% was used as a test set. Up to 300 epochs were trained, and the change in loss value according to epoch progress during training is shown in Figure 6. The smallest loss value was shown at the 32nd epoch, where the loss value of the test set was 0.00878 (0.88%) and the accuracy value was 0.9794 (98%).

The confusion matrix for cough detection is shown in Figure 7 when the performance evaluation of the 32nd epoch's AI model is performed. The rate of detecting real cough sounds as cough was 95.12%, and the rate of classifying real non-cough sounds as non-cough was 100%. This seems to make the detection of cough sounds very rigorous, and sounds that are not obvious cough are classified as non-cough sounds. This seems to be due to the fact that a number of sounds similar to coughing (ex: clearing one's throat, laughing) are included among the non-cough sounds in the training data. No real non-cough sound was mistaken for coughing.

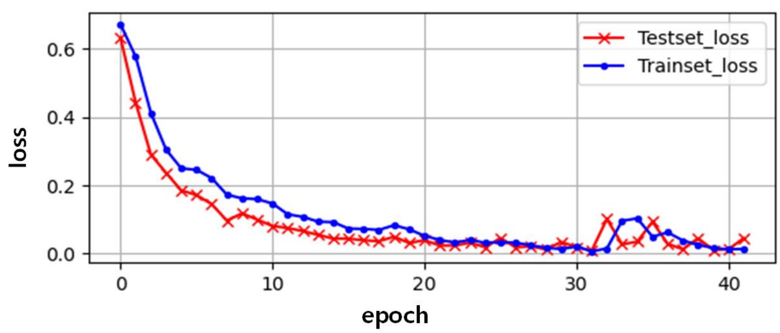

Figure 6. Change of loss value

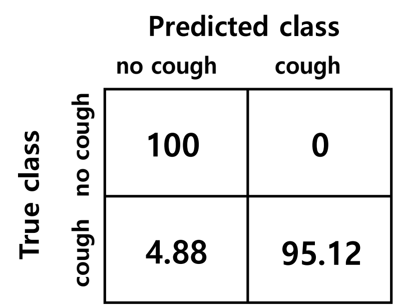

Figure 7. Confusion matrix

Table 1 shows the performance metrics of the cough detection system developed in this study. As shown in the experimental results, even if the cough sound is distorted in the respiratory protection, it is possible to effectively detect cough using the AI model.

Table 1. Performance metrics for cough detection

F1-Score (%)	Sensitivity (%)	Specificity (%)	Precision (%)	Accuracy (%)
97.5	95.12	100	100	97.94

5. Conclusion

In this paper, we designed and implemented a system to detect cough in a respirator equipped with a smart sensor. Because the cough sound is distorted in the respirator, accuracy cannot be guaranteed in the AI model learned from the cough sound in an open environment. In this study, a microphone sensor and a communication module were attached to the non-motorized hooded respirator to detect sound and transmit it to the data server through a smart app, and the data server used the AI model to determine whether the transmitted sound was coughing or not.

In order to separate the cough sound from the continuous audio data, sound frames were analyzed in units of 10msec, and when the loudness of the frame exceeded the threshold value, the 300msec sound section starting from the frame was extracted as a candidate cough sound. In order to efficiently classify sound data, it was converted into Mel-spectrogram data, and the CNN model was trained using this data, and its performance was evaluated.

The developed cough detection system had a sensitivity of 95.12% and a specificity of 100%, and an overall accuracy of 97.94%. If the AI model is trained by acquiring more cough data, it will show higher accuracy.

References

[1] World Health Organization, Coronavirus disease (COVID-19) pandemic. https://www.who.int/emergencies/diseases/novel-coronavir
[2] U.S. Department of Health & Human Services, Personal Protective Equipment. https://chemm.nlm.nih.gov/ppe.htm
[3] A. Tabah, M. Ramanan, K.B. Laupland, N. Buetti, A. Cortegiani, J. Mellinghoff, A.C. Morris, L. Camporota, N. Zappella, M. Elhadi, P. Povoa, K. Amrein, G. Vidal, L. Derde, M. Bassetti, G. Francois, N.S. Kai, J.J. De Waele, and the PPE-SAFE contributors, “Personal protective equipment and intensive care unit healthcare worker safety in the COVID-19 era (PPE-SAFE): An international survey,” Journal of Critical Care, Vol. 59, pp. 70–75, 2020. DOI: https://doi.org/10.1016/j.jcrc.2020.06.005
[4] The Prakash Lab at Stanford University, The Pneumask Project. https://www.pneumask.org
[5] F. Sasangohar, S. L. Jones, F. N. Masud, F. S. Vahidy, and B. A. Kash, “Provider Burnout and Fatigue During the COVID-19 Pandemic: Lessons Learned From a High-Volume Intensive Care Unit,” Anesthesia and analgesia, Vol. 131, pp. 106-111, 2020. DOI: https://doi.org/10.1213/ANE.0000000000004866
[6] A. Imran, I. Posokhova, H. N. Qureshi, U. Masood, M. S. Riaz, K. Ali, C. N. John, MD I. Hussain, and M. Nabeel, “AI4COVID-19: AI enabled preliminary diagnosis for COVID-19 from cough samples via an app,” Informatics in Medicine Unlocked, Vol. 20, p. 100378, 2020. DOI: https://doi.org/10.1016/j.imu.2020.100378
[7] H. B. Carlos, M. Jesús, P. Zeeshan, S. J. R. Luis, and C. H. Pablo, “Efficient computation of image moments for robust cough detection using smartphones,” Computers in biology and medicine, Vol. 100, pp. 176-185, 2018. DOI: https://doi.org/10.1016/j.compbiomed.2018.07.003.
[8] M. You, Z. Liu, C. Chen, J. Liu, X. Xu, and Z. Qiu, “Cough detection by ensembling multiple frequency subband features,” Biomedical Signal Processing and Control, Vol. 33, pp. 132-140, 2017. DOI: https://doi.org/10.1016/j.bspc.2016.11.005.
[9] G. Rudraraju, S. D. Palreddy, B. Mamidgi, N. R. Sripada, Y. P. Sai, V. N. Kumar, and S. Haranath, “Cough sound analysis and objective correlation with spirometry and clinical diagnosis,” Informatics in Medicine Unlocked, Vol. 19, p. 100319, 2020. DOI: https://doi.org/10.1016/j.imu.2020.100319.
[10] B. Bozkurt, I. Germanakis, and Y. Stylianou, “A study of time-frequency features for CNN-based automatic heart sound classification for pathology detection,” Computers in Biology and Medicine, Vol. 100, pp. 132-143, Sep. 2018. DOI: https://doi.org/10.1016/j.compbiomed.2018.06.026
[11] J. Salamon and J. P. Bello, "Deep convolutional neural networks and data augmentation for environmental sound classification," IEEE Signal Processing Letters, Vol. 24, pp. 279-283, Jan. 2017. DOI: https://doi.org/10.1109/LSP.2017.2657381