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Classification Type of Asynchrony Breathing Image Using 2-Dimensional Convolutional Neural Network
(2023) *9th 2023 International Conference on Control, Decision and Information Technologies, CoDIT 2023*, pp. 2281-2286.

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Abstract
Asynchrony breathing (AB) refers to a situation where the patient's breathing does not align with the mechanical ventilator (MV), which can have a detrimental effect on the patient's recovery. A few types of AB make it difficult for clinicians to identify and manage MV properly. Hence, there is a need to develop a method that can classify the type of AB in MV patients. In this study, a 2- dimensional (2D) convolutional neural network (CNN) method is presented to classify the type of AB based on the input image of the airway pressure. A total of 866 images of airway pressure were analysed in this study, and 4 types of AB were classified: 1) double triggering (DT); 2) reverse triggering (RT); 3) delayed triggering (DC); and 4) premature cycling (PC). Two types of activation functions for classification purposes, SoftMax and Sigmoid, were compared based on performances. Results show SoftMax produced a higher accuracy of 98.5% with a training dataset of 70% and a testing dataset of 30% of the data. In contrast, the Sigmoid function produced an accuracy of 98.1 % when trained and tested with the same dataset. Furthermore, this 2D-CNN model produced a range of accuracy between 89% and 96% in classifying the type of AB, with the highest accuracy of 96% in classifying DT. Overall, the developed CNN model, based on the input image of airway pressure, accurately extracts critical and unique features to precisely classify various types of AB, which could help clinicians in managing MV patients. © 2023 IEEE.

Index Keywords
Convolutional neural networks, Image classification, Neural network models, Patient rehabilitation, Statistical tests; 2 - Dimensional, Airway pressures, Asynchrony, Convolutional neural network, High-accuracy, Input image, Mechanical, Neural network method, Neural network model, Patient breathing; Convolution

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