Classification Patient-Ventilator Asynchrony with Dual-Input Convolutional Neural Network

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Abstract: Mechanical ventilated respiratory failure patients may experience asynchronous breathing (AB). Frequent occurrence of AB may impose detrimental effect towards patient's condition, however, there is lack of autonomous AB detection approach impedes the explication of aetiology of AB causing underestimation of the impact of AB. This research presents a machine learning approach, a dual input convolutional neural network (CNN) to identify 5 types of AB and normal breathing by accepting both airway pressure and flow waveform profiles concurrently. The model was trained with 6,000 breathing cycles and validated with 1,800 isolated data collected from clinical trials. Results show that the trained model achieved a median accuracy of 98.6% in the 5-fold cross-validation scheme. When validated with unseen patient's data the trained model achieved an accuracy median of 96.2%. However, the model was found to misidentify premature cycling with reverse triggering. The results suggest that it may be difficult to clearly distinguish ABs with similar features and should be trained with more data. Nonetheless, this research demonstrated that a dual input CNN model able to accurately categorise AB which can potentially aid clinicians to better understand a patient's condition during treatment.

Keywords: Asynchrony, Mechanical ventilation, Machine Learning, Convolution Neural Network.

1. INTRODUCTION

Mechanical ventilation (MV) is a life-saving treatment for intensive care patients with acute respiratory failure. However, this form of medical intervention may be compromised if there is frequent occurrence of asynchronous breathing (AB). AB is a medical condition characterised as 'fighting against ventilatory support' in MV patients (Sassoon and Foster, 2001). Frequent occurrence of AB may impose detrimental impact towards patient's recovery, increases sedative drugs usage, lengthen ICU stay and worsen mortality rate (Blanch et al., 2015). While there are seven known types of AB with each AB poses unique asynchrony characteristics and patterns (Nilsestuen and Hargett, Mellott et al., 2014), the adverse effect of AB towards patient's recovery is still under-recognised due to limited methods to detect and classify them during MV treatment. As a result, the conventional approach to AB detection often relies and involves labour clinical bedside observation of the airway pressure and flow waveform (Georgopoulos et al., 2006) to compute asynchronous index (AI) (Chao et al., 1997). While AI is the assessment to the quality of patient-ventilator interaction, slow visual inspection and interpretation of breathing cycle severely impedes the assessment. Furthermore, the occurrence of AB is spontaneous. Thus, with the prevalence of AB, manual computation of PVI assessment is not applicable in a time critical clinical environment. Therefore, an automated to detect and classify AB can potentially aid clinicians to determine the causal mechanism to eradicate AB occurrence (de Haro et al., 2019).

Continuous efforts have been made in the recent years to detect AB automatically. For example, Akouminaki et al. (2014) monitored AB via the measurement of changes in oesophageal pressure. Sinderby et al. (2013) determined the occurrence of AB with the use of electrical diaphragm activity measured through electrodes incorporated into a nasogastric tube. Despite these methods were able to accurately detect AB, insertion of balloon catheter or additional probes into oesophageal tract is uncommon and not part of ICU routine. Gutierrez et al. (2011) presented a method of evaluating asynchrony via spectral analysis of airway flow waveform. This approach is automatic and non-invasive, but the absence of airway pressure consideration in the analysis may lead to lower AB detection sensitivity and specificity. Similarly, there are AB detection methods that were developed using rule-based methods; Better care (Blanch et al., 2012) and Time-varying elastance (Poole et al., 2014) and ALIEN (Chiew et al., 2015). However, rule-based methods are susceptible to inaccurate and ambiguous perception for selection of threshold parameter, which is increasingly challenging to account for intra and inter variability in patient data.

The emergence of machine learning methods has observed major advancement in AB detection. Loo et al. (2018) proposed convolutional neural network (CNN) machine learning algorithm to detect the presence of AB, but the method does not perform sub-classification. Zhang et al. (2020) implemented a two-layer long short-term memory machine learning approach to detect the presence 2 types of AB. Despite the model achieved remarkable performance; the method is limited to two types of asynchronies detection. Gholami et al. (2018) proposed a random forests machine learning technique to identify cycling asynchrony by extracting engineered features that defines the asynchrony. However, their non-uniform distribution of datasets may introduce biasness to the developed neural network model. Thus, there is a need of a machine learning model that can detect various forms of AB.

In this research, we have developed an optimised dual-input convolutional neural network (CNN) model to perform a larger scale of AB detection that can subcategorise into normal breathing cycle with 5 different ABs using only airway pressure and flow waveform profile. The proposed CNN model is able to capture the morphological characteristics of AB types, and to classify them with high accuracy.

2. METHODOLOGY

2.1 Patient Data

Retrospective airway pressure and flow of 23 MV patients from an observational trial (Chiew et al., 2018a) were used for this research. The data were collected at 50 Hz using a CURE data acquisition system (Szlavecz et al., 2014). The trial was approved by the International Islamic University Malaysia Medical Center Research Ethics Committee (Ref: IREC666).

2.2 Data Annotation

Detection and classification AB can often be confusing (Pan et al., 2021) due to vague erratic asynchrony features. Therefore, identification of AB at clinical beside usually conducted by trained clinicians which only focuses on apparent features on the airway pressure and flow waveform profile. The ability of CNN to extract these critical features automatically from the given patient's data during training eliminates the resources to train clinicians to identify them. Figure 1 depicts different type of AB with each AB possesses its unique identification features detailed in Table 1.

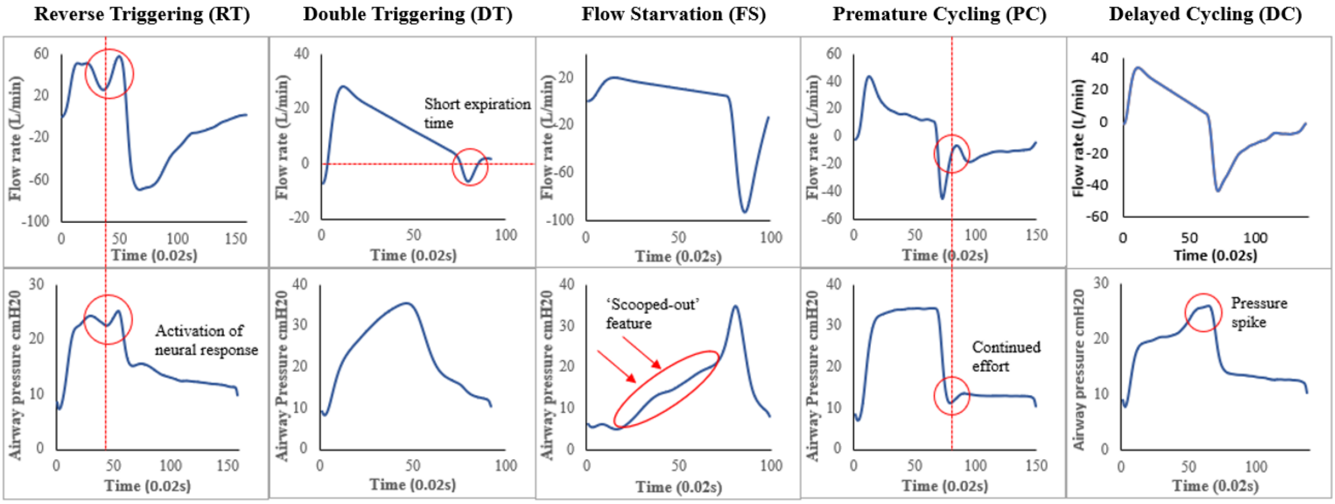

Fig. 1. Different types of AB based on the retrospective patient airway pressure and flow waveform.

Table 1. Sub-types of AB, their definitions and identification features

AB Type	Definition	Identification features
Reverse Triggering **(RT)**	Mechanically insufflation-triggered breathing due to activation of neural response of the lung.	Manifested as a drop in airway pressure midway of inspiration phase.
Double Triggering **(DT)**	Continued effort resulting stacked breathes; when one inspiration cycle ends, another inspiratory effort is triggered due to high patient demand.	Evident when the expiration time is less than one third of inspiration time. On pressure-time waveform, the pressure profile will span wider due to significantly longer inspiratory effort.
Flow Starvation **(FS)**	Persistence of inspiratory effort due to inadequate flow delivery from the MV.	Visually recognised by identifying the 'scooped out' or 'sucked-down' feature on the pressure waveform which indicates excessive diaphragmatic muscle loading.
Premature Cycling **(PC)**	Persistence of inspiratory effort due to early termination of inspiratory support from MV.	Manifested as an upward concavity on pressure waveform and downward concavity on the flow waveform at the initiation of expiration phase.
Delay Cycling **(DC)**	Prolongation of inspiration phase due to late termination of inspiratory supported breath even after the activation of patient's expiratory muscle.	Exhibits itself in the form of 'pressure-spike' or 'pressure-tent' prior to the initiation of expiration phase which represents the accumulation of air.

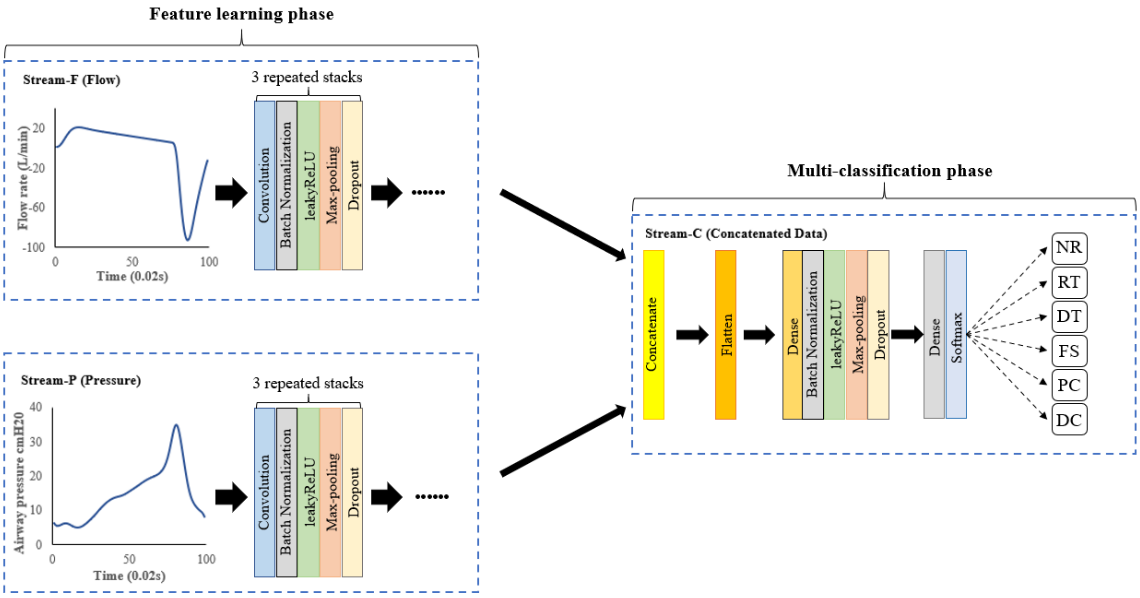

Fig. 2. Overview of dual-input CNN model architecture developed in this study.

In this study, a total of 42,245 breathing cycles were manually annotated and categorised into five different types of AB namely reverse triggering (RT), double triggering (DT), flow starvation (FS), premature cycling (PC) and delayed cycling (DC) as well as normal breathing (NR) cycle. We established two datasets with one for model training while the other to validate the performance of the trained model. For training dataset, each category consists of 1,000 training data whereas, the validation dataset consists of 300 breathing cycle for each category. The validation datasets are randomly selected and segregated from the training datasets. In other words, the performance of the trained model will be assessed with unseen actual patient's data. The specifics of the manually annotated datasets are presented in Table 2. It should be noted that the uniform distributed datasets are critical to ensure that the network demonstrates unbiased and accurate training, and predictive performance.

Table 2. Specifics of patient data annotation

	Dataset 1 (Training)	Dataset 2 (Validation)
Total Data screened	29745	12500
RT	1384 (1000)	1651(300)
DT	1234 (1000)	430 (300)
FS	1004 (1000)	325 (300)
PC	1013 (1000)	380 (300)
DC	1009 (1000)	382 (300)
(Normal/Noise)	24101 (1000)	9332 (300)

2.3 Convolution Neural Network and Architecture

Convolutional neural network is an artificial neural network widely deployed to perform multi-classification (Dhillon and Verma, 2020). The building blocks of convolution layers alternating with subsampling layer imitate the structure of a visual cortex which comprises of both complex and simple cells (O'Shea and Nash, 2015). These features enable CNN to extract and 'understand' high-level essential patterns automatically via its adaptable parameters in the convolution layer during training.

In this research, we developed a dual input CNN model to accept one-dimensional structured airway pressure and flow waveforms inputs. The dual-input CNN model is designed to extract localised high-level features on the both the airway pressure and flow waveform that describes the distinct morphological characteristic of different subclasses of AB according to the definition in Table 1. This approach imitates the clinical diagnosis of AB via analysing patterns in both airway pressure and flow waveform profile more accurately. The overview architecture of the CNN model is depicted in Figure 2 with each of its configuration listed in Table 3.

Table 3. Properties of the proposed CNN architecture

Stream	Layer	Properties
F, P	Input	180x1
	Convolution-1	32 filters, 3 strides
	Batch Normalisation-1	
	Activation-1	LReLU ($a = 0.1$)
	Max-pooling-1	2
	Dropout-1	0.25
	Convolution-2	32, 3
	Batch Normalisation-2	
	Activation-2	LReLU ($a = 0.1$)
	Max-pooling-2	2
	Dropout-2	0.25
	Convolution-3	32, 3
	Batch Normalisation-3	
	Activation-3	LReLU ($a = 0.1$)
	Max-pooling-3	2
	Dropout-3	0.4
C	Fully Connected	512
	Batch Normalisation	
	Activation	LReLU ($a = 0.1$)
	Dropout	0.25
	Fully Connected	0.5
	Activation	Softmax

2.3.1 *Input Layer (Stream-F and Stream-P)*

The dual-input CNN model is branched into two streams, namely Stream-F (Flow) and Stream-P (Pressure) which accepts flow and airway pressure waveform respectively. The magnitude of both airway pressure and flow waveform profile are normalised to 0 and 1 as well as the datapoints are resample to 180 data points to standardise the training input data length. Pre-processing is necessary as it accelerates the convergence during training (Jin et al., 2015).

2.3.2 *Convolutional Layer*

Convolution layer is responsible in crucial localised features extraction from the connected input via the application of convolving kernels. The operation of convolution in convolutional layer is expressed in Equation 1, where f denotes the activation function, * denotes convolution operation, w_i represents the weight tensor at $i-th$ neuron, x_i represents the input vector at $i-th$ neuron and, b denotes the bias value. In this research, each convolutional layer consists of 32 filers with kernel size equals to 3 with stride of 1.

$$y = f\left(\sum w_i * x_i + b\right) \qquad (1)$$

2.3.3 *Activation Function and Batch Normalisation*

Activation function and batch normalisation both play an important role in ensuring the input elements are capped within a manageable range by normalising and rectifying non-acceptable range of values (Nwankpa et al., 2018). In this study, all the outputs from convolution layer undergo batch-normalisation operation followed by activation function namely leaky rectified linear unit (LReLU). While the linear behaviour and sparsity representation of ReLU has demonstrated computational efficient in CNN models (Krizhevsky et al., 2017), LReLU is preferred in our model due to its ability to avoid 'dying ReLU' due to deterrence of learning gradient recovery if output is activated as zero (Maas, 2013). The piecewise function is expressed in Equation 2 where a denotes the allowable negative slope coefficient and x and y is the input and output respectively. On the other hand, Softmax activation function which calculates the probability distribution of each AB type over the total number classes to constrained predicted outcome within 0 and 1 is applied to the output of the CNN model.

$$y = \begin{cases} x, & if\ x > 0 \\ ax, & if\ x \leq 0 \end{cases} \qquad (2)$$

2.3.4 *Max-pooling Layer and Dropout Layer*

Pooling layers serve the purpose to decrease the dimension of features gradually to control overfitting and computational complexity (O'Shea and Nash, 2015). The operation of max-pooling is expressed, where the output is the maximum element of the non-overlapping portioned sub-regions. On the other hand, dropout layer improves generalisation ability of the CNN model by omitting few percentage of neurons randomly during training to prevent the overfitting (Srivastava et al., 2014).

2.3.5 *Classification (Stream-C)*

This layer merges and flattens the multi-dimensional extracted vital features from *Stream-F* and *Stream-P*. This allows the trainable parameters in the neurons to 'learn' to classify breathing cycle into 6 different categories. A total of 2 fully connected layers with 512 and 6 output neurons respectively contains trainable weights and bias. Similarly, each neuron undergoes batch-normalisation and dropout layer to control overfitting. Categorical cross-entropy loss function was implemented to update the parameters with Adam as optimiser.

2.4 *Computational Setup and Training Process*

The entire development and training of CNN model in this study was developed using Keras deep learning library which allows the utilisation of Graphical Processing Unit (GPU) to train CNN on Python programming language. In addition, all simulations were trained on Intel Core i7-9750H, 16GB random access memory and a NVIDIA GeForce RTX 2060. To ensure reproducibility, the models were initialised with the same random seed and trained with 50 epochs.

2.5 *CNN Performance Evaluation*

To assess the performance of the CNN model, a 5-fold cross validation technique is implemented as illustrated in Figure 3. 5-fold cross validation segregates the Dataset 1 into 5 mutually exclusive set, whereby 4 of the sets are used for CNN training while the remaining unseen datasets are used to evaluate the performance of the trained model. The 4 of the datasets are split internally into 70:30 ratio for training and validation during training. This process is repeated until each of the 5 mutually exclusive sets are tested. The average accuracy of the trained model evaluated via K-fold analysis will help to determine the consistency of the CNN model performance.

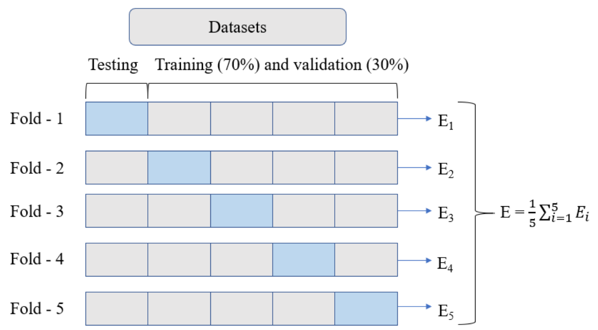

Fig. 3. 5-fold cross validation scheme applied to test the robustness of the proposed model.

Subsequently, the model with highest accuracy among the K-fold will be selected to assess its performance with Dataset 2. This is to evaluate the model's performance with unseen actual patient data via the computation of accuracy, sensitivity and specificity using Equations (3-5). In this study, the sensitivity and specificity analysis use one against all approach whereby NR is considered as condition positive while the rest is considered as condition negative. In other words, true positive, TP denotes as the NR correctly identified and true negative, TN denotes as any AB correctly identified as AB. False positive, FP and false negative, FN represents the falsely identified AB as NB and vice versa respectively.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (3)$$

$$Sensitivity = \frac{TP}{TP+FN} \quad (4)$$

$$Specificity = \frac{TN}{TN+FP} \quad (5)$$

3. RESULTS

The results for the 5-fold cross-validation are presented in Table 4 with an average of 97% for all validation dataset cases. It also shows that the first K-fold iteration attained highest accuracy. The highest accuracy model was then selected to perform classification using total of 1,800 unseen patient's data. Besides that, the confusion metrics shown in Table 5 shows that CNN yielded lowest accuracy when classifying PC with only 53.7% accuracy, whereas CNN attained near 100% accuracy when detecting DC and DT. Overall, CNN achieved 100% and 98.7% sensitivity and specificity respectively when assessing validation dataset.

Table 4. Accuracy of trained model for each k-fold

K-fold iteration	Accuracy (%)
1	98.8
2	98.7
3	97.5
4	90.4
5	98.6
Median	98.6

Table 5. Performance assessment of the trained CNN tabulated in confusion matrix

		Predicted						Accuracy (%)
		NR	RT	FS	PC	DC	DT	
Actual	NR	281	9	0	0	10	0	93.7
	RT	0	276	0	0	24	0	92.0
	FS	0	0	296	0	4	0	98.7
	PC	0	139	0	161	0	0	53.7
	DC	0	1	0	0	299	0	99.7
	DT	0	1	0	0	0	299	99.7
Median [Interquartile range]								96.2 [92.0–99.7]

4. DISCUSSION

This developed CNN architecture is one of the few AB detection machine learning approach capable of categorising 5 types of AB and identifying normal breathing by using both airway pressure and flow waveform profile as inputs. The integration of both airway pressure and flow waveform profile during training which is essential and necessary to accurately define and characterise different types of AB.

Table 4 shows that the consistent accuracy yielded from 5-fold cross-validation implies the robustness and great ability of CNN to extract critical unique features to identify different types of AB accurately. However, the results shown in Table 5 shows low accuracy when detecting PC, and it is often confused with RT. We speculate that low accuracy could be due to the subtle PC features is very similar to a RT as shown in Figure 1 (Pan et al., 2021, Baedorf Kassis et al., 2021). Therefore, training the CNN with additional data or modifying the number of convolutional layers to extract these indistinct features could potentially improve the performance.

While the CNN model presented in this research work were able to perform well, there are some limitations that ought to be addressed. The present work mainly involves the study population of the MV patients ventilated using SIMV mode. As the manifestation of the breathing cycles or AB is largely dependent on the MV modes (Baedorf Kassis et al., 2021). Thus, implementing this algorithm at the bedside using a monitoring system (Ng et al., 2020, Ng et al., 2021)to detect AB autonomously still requires additional effort to develop CNN model to detect AB present in different MV modes.

This CNN model was not trained to identify the presence of ineffective triggering due to insufficient datasets. Despite existing techniques suggest that resampling data may be able to cope with imbalance dataset (Rehm et al., 2018), we believe that collecting more data is more favourable. Therefore, to avoid non-uniform distribution of datasets which might introduce model bias, IE detection is removed. Similarly, auto-triggering (AT) is not included in the datasets due to the lack of additional information such as oesophageal pressure or electrical activity of diaphragm (Pham et al., 2021). Nonetheless, the CNN model proposed here is able to detect the presence of AB. Further studies should be focused in examining the magnitude of different types of AB and their impact towards patient's condition and their outcome (Chiew et al., 2018b, Loo et al., 2021).

5. CONCLUSION

The CNN model developed in this study showed promising results with the ability to detect and classify 5 types of AB and normal breathing with an average accuracy of around 90%. Its potential implementation in clinical environment could help clinicians to better understand patient's condition during treatment and help in managing patient-ventilator interaction.

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